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Explanatory factors for Marine Corps aviation maintenance performance

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THESIS

EXPLANATORY FACTORS FOR MARINE CORPS AVIATION MAINTENANCE PERFORMANCE

by

Gregory L. Chesterton

September 2005

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13. ABSTRACT (maximum 200 words)

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Thirty months of data were collected for thirteen active duty Marine Corps F/A-18 squadrons. Regression is used to model man-hours per maintenance action as a linear combination of explanatory variables that describe the squadrons in terms of manpower, inventory, and ETS metrics. The test for significance indicates that the model developed in this study is highly likely to have better explanatory power than an intercept-only (average) estimate of the response variable. The study concludes with recommendations for data collection methods that would facilitate the correlation of squadron characteristics to ETS utilization. Critical to the success of this approach is the linkage of ETS utilization to specific squadron maintenance activities, and the development of methods to quantify maintainer training currency.

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EXPLANATORY FACTORS FOR MARINE CORPS AVIATION MAINTENANCE PERFORMANCE

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LIST OF ABBREVIATIONS AND ACRONYMS

AFLMA	Air Force Logistics Management Agency
AIC	Akaike Information Criterion
AIRRS	Aircraft Inventory Readiness And Reporting System
ANOVA	Analysis of Variance
AWM	Awaiting Maintenance
AWP	Awaiting Parts
CJCS	Chairman Joint Chiefs of Staff
CONUS	Continental United States
CVN	Aircraft Carrier, Nuclear Powered
DECKPLATE	Decision Knowledge Programming for Logistics Analysis and Technical Evaluation
EIS	Equipment in Service
ELAR	ETS Local Assistance Request
EMT	Elapsed Maintenance Time
ETS	Engineering and Technical Services
FMC	Full Mission Capable
GSORTS	Global Status of Resources and Training System
JCN	Job Control Number
MAF	Maintenance Action Form
MC	Mission Capable
MCAS	Marine Corps Air Station
MCTFS	Marine Corps Total Force System
MDS	Maintenance Data System
MESM	Mission Essential Subsystem
MOS	Military Occupational Specialty
NAESU	Naval Aviation Engineering Service Unit
NALCOMIS	Naval Aviation Logistics Command Information System
NATEC	Naval Air Technical Data and Engineering Service Command
NAVAIR	Naval Air Systems Command
NMC	Not Mission Capable
NMCM	Not Mission Capable Maintenance
NMCMS	Not Mission Capable Maintenance, Scheduled
NMCMU	Not Mission Capable Maintenance, Unscheduled
NMCS	Not Mission Capable Supply
NTR	NAESU Technical Report
OJT	On the Job Training
PDS	Personnel Data System
PMC	Partial Mission Capable
QQ	Quantile-quantile
REMIS	Reliability and Maintainability Information System
SAFE	Structural Appraisal of Fatigue Effects
SCIR	Subsystem Capability and Impact Reporting

T&R	Training and Readiness
TD	Technical Directive
TDSA	Technical Directive Status Accounting
TEC	Type Equipment Code
TRMS	Type Commander (TYCOM) Readiness Management System
UDP	Unit Deployment Program

EXECUTIVE SUMMARY

The performance and expertise of Naval aviation squadrons is closely tied to the performance of their maintenance teams. Aircraft that cannot fly or operate in a fully functional manner due to inadequate maintenance seriously harms mission capability. It is useful, therefore, to identify factors related to a squadron's mission, and the personnel and assets at its disposal, which help to explain the performance of their maintainers.

How should maintainer performance be measured? The speed and correctness with which maintenance actions are conducted are important aspects of performance, although they may be difficult to quantify. External factors, such as the availability of repair parts and the operations tempo of the squadron, also affect measures that may be used to describe maintenance performance. Therefore, we use *man-hours per maintenance action* as a measure of performance, due to its direct relationship to the actions of the maintainers, and to limits the effects of external confounding factors.

In this thesis we examine monthly data of thirteen Marine Corps F/A-18 squadrons taken over a two-year period to identify squadron characteristics that are important predictors of *man-hours per maintenance action*. Also, we gain insight on maintenance performance from data collected on the squadrons' utilization of engineering and technical services. Specifically, we address the following research questions:

1. Which squadron characteristics have a detectable contribution to the variability of the performance measure *man-hours per maintenance action*?

2. How much additional variability is explained by the squadron that is not accounted for by the squadron characteristics already considered?

3. Is there a time-of-year effect for the performance of the squadrons?

4. What additional metrics not currently available would most likely be useful in an explanatory model of maintenance performance?

5. What data collection methods, if any, would be likely to improve the ability of NATEC managers to correlate squadron characteristics to tech rep measures of performance?

Flight operations rely on a maintenance workforce that can meet the demands of a flight schedule by performing preventive and corrective maintenance. If necessary, maintenance personnel may request the expertise offered by government civil service or civilian contracted personnel, known as technical representatives ("tech reps"), who provide engineering and technical services (ETS) in the form of on-the-job training, troubleshooting, and additional training.

We integrate data collected from several independent Department of Defense sources on maintenance actions, personnel, aircraft inventory, and technical services utilization to derive metrics that allow performance and other characteristics to be quantified for the thirteen Marine Corps F/A-18 squadrons in the scope of our study. For each squadron, approximately 30 months of observations are collected to quantify performance and descriptive characteristics. Personnel metrics quantify the experience levels and turnover rates of the squadrons on a monthly basis. Experience is measured by the number of months that an individual maintainer has spent in a squadron and in the Marine Corps. Inventory metrics characterize the ages and type of F/A-18 aircraft maintained by a squadron. Technical services metrics quantify the type and volume of ETS activity in a squadron for a given month. We also capture the operational context in which a squadron performs its mission: combat operations, unit deployment program, a carrier deployment, or a between-deployment phase.

Exploratory data analysis shows that performance cannot be explained by any single squadron characteristic. Linear regression is used to model *man-hours per maintenance action* as a linear combination of explanatory variables. A test for significance indicates that the model is highly likely to explain the variability of the response variable when compared to an intercept-only (average response) model. Stepwise reduction is used to reduce the model to a simpler model that retains most of its explanatory power. This reduced model indicates that five of the explanatory variables are statistically significant in explaining *man-hours per maintenance action*: *type equipment code* (TEC), *average aircraft hours in service*, *median months in squadron*, *location*, and *deployment status*. Nonetheless, this model explains only 20 percent of the variability of the response variable. By including a factor that identifies the particular squadron, the explanatory capability of the model is increased to approximately 50 percent. This suggests that there are important differences between the squadrons that explain performance but that are not captured in the variables included in this study. The final model takes the form

$$\ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \varepsilon_{s,t}$$

Where

$Y_{s,t} =$ man-hours per maintenance action, squadron s, month t
$X_{1,s,t} =$ type equipment code
$X_{2,s,t} =$ average aircraft hours in service
$X_{3,s,t} =$ location
$X_{4,s,t} =$ months in squadron, median
$X_{5,s,t} =$ deployment status
$\varepsilon_{s,t} =$ residual
$k =$ number of variables
$s =$ squadron
$t =$ month

For those factors found to be significant, the coefficients provide some insight as to their positive or negative correlation with the performance variable. The performance of the maintainers, expressed as *man-hours per maintenance action*, improves (decreases) with increased experience of the maintainers (higher values of *months in squadron*).

The data do not indicate that there is a time-of-year effect in *man-hours per maintenance action*. However, there is detectable serial correlation in the residuals from the regression model, suggesting that there may be temporal effects that could be handled with a generalized least squares approach.

The thesis is constrained primarily by the short time frame of the study, a result of the attempt to include the relatively recent ETS data in the analysis. At the time of this writing, ELAR is a nascent database with records of varying degrees of completeness. In a broader sense, NATEC's ELAR initiative and this thesis are both part of a larger effort to link maintenance utilization metrics, one of which is ETS utilization, with maintenance performance measures. As the quality and scope of ELAR data reporting improve, ELAR will play a more effective role in establishing a linkage between ETS utilization and Naval aviation maintenance performance. In addition, the explanatory power of the model would likely improve with more accurate model estimates obtained from data collected over a longer period of time, and from the inclusion of maintenance performance metrics not currently available in the maintenance data system.

The study concludes with recommendations for data improvement. We determine that a critical requirement for making the tech rep data more valuable to analysis is the linking of their activity to specific squadron maintenance activity—through NALCOMIS, for example. This will allow a direct measure of their impact on readiness and performance in a way similar to other maintenance factors.

Also vital to the description of squadron capability is the development of methods to quantify the training currency of the maintainers. This will allow real-time assessment of maintenance proficiency and will highlight skill areas that need renewed training attention.

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I. INTRODUCTION

> *When you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind: it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science, what ever the matter may be.*
>
> Lord Kelvin 1824-1907, British scientist

A. BACKGROUND

1. The Value of Human Capital

We have evolved from an industrial age during which assets were tangible, countable, and of a measurable value, to a modern era, characterized by the need for and availability of information. Today's organizations are unique in that a large percentage of their worth lies in the value of their human capital rather than its physical assets. In the past three decades, both public and private industry has been forced to streamline operations in the face of reduced budgets, smaller margins, and focused competition. At the heart of this struggle is the need to measure the value of that human capital—its output and its capacity to produce.

This problem is not confined to the corporate world of the balance sheet and the profit and loss statement; with limited resources, the U.S. Department of Defense also needs to maximize the output of its personnel and equipment. The services have seen an additional focus on force transformation [Rumsfeld, 2003]; such a level of productivity demands streamlined, optimized operations. In the face of these requirements, leaders strive to develop metrics that will enable them to accurately measure productivity and the factors that improve it.

2. Aviation Maintenance

A functional area under continued scrutiny in both the civilian and military sectors is that of aviation maintenance. Although their missions are different, as are the environments in which their missions are executed, both military and civilian flight operations rely on a maintenance workforce that can meet the demands of a flight schedule. Civilian organizations may see sub-optimal performance reflected in reduced profit. The armed services, on the other hand, may not see immediate ramifications of poor performance. The ultimate test for any military unit is combat, but with sporadic combat operations, the consequences of inferior maintenance performance are not always apparent.

An understanding of the functions of aviation maintenance helps to explain how analysts attempt to measure performance. In the most basic terms, the mission of any aviation maintenance organization is straightforward: to maintain aircraft through routine scheduled maintenance and to repair aircraft that become inoperable due to normal use and wear. Aviation maintenance managers must strike the proper balance between scheduled and unscheduled maintenance to meet the demands of a squadron's flight schedule while preserving the long-term health of the fleet.

All military flying units have the ability to perform a limited level of maintenance on their own inventory of aircraft. During the course of an operating day, any aircraft malfunctions that are not discovered by the maintainers through routine inspection are usually brought to their attention by the aircrew that discover them either before, during, or after a flight. The aircrew and maintenance personnel record these discrepancies electronically, which initiates the maintenance process required to address the discrepancy. The discrepancy record also contains the repair time, man-hours expended, parts removed and replaced, and other descriptive information. The purpose of such data collection is to allow maintenance analysts to identify trends that may point to problem areas such as high-fault subsystems and repeat discrepancies.

3. Engineering and Technical Services

Throughout the course of maintenance being performed on the aircraft—a process that ends with the action being approved by a responsible authority—maintenance personnel ("maintainers") diagnose the discrepancy by referencing their own training and experience, technical publications with prescribed troubleshooting techniques, and other personnel who may have performed similar maintenance in the past. If necessary, maintainers may request the expertise offered by government civil service or civilian contracted personnel who provide engineering and technical services. In addition to providing on-site troubleshooting expertise, these service providers, referred to as “tech reps” for short, supplement the training of maintenance personnel by providing more formal instruction in classroom settings and in squadron work centers.

In the Department of the Navy, tech reps are managed by the Naval Air Technical Data and Engineering Service Command (NATEC). The origin of what is now NATEC—formerly known as NAESU (Naval Aviation Engineering Service Unit)—was the response, in WWII, to the shortage of trained electronics technicians. Now responsible for all areas of engineering and technical data, NATEC documents requests for assistance in a database called ELAR (ETS Local Assistance Request). ELAR records are generally initiated by the maintenance activity that requests NATEC support. The requests are approved and apportioned by a NATEC detachment supervisor, and are finalized with brief customer satisfaction comments from the originator upon completion of the action.

NATEC’s customers—the flying squadrons of the Navy and Marine Corps—have grown accustomed to having the availability of the tech reps at their disposal even during operational deployments. However, NATEC must allocate its limited resources to meet the competing demands of its customers. Such an allocation involves determining the best performance value return on manpower resource investment. NATEC managers, like other maintenance managers, seek to define those metrics that best measure the health of the squadrons in order to optimize the distribution of their limited resources and maximize customer satisfaction. Analyses of tech rep support [Boynton, Seiden, and Vaughan 1995; Boynton and Vaughan,1998] describe the difficulties of quantifying tech reps’ contributions to aviation readiness. NATEC implemented ELAR in August 2003 in an effort to address this problem. Prior to ELAR, the Navy lacked a systematic data-collection tool for tracking the utilization of technical services by its aviation maintainers. In the absence of such data it is impossible to correlate aviation maintainer performance to the usage of these services. At the time of this writing, ELAR contains approximately two years of data, but its early records are insufficiently complete to conduct meaningful statistical analyses linking ETS utilization to maintenance outcomes. We view the continual improvement of ELAR and this thesis as parts of a larger effort to link characteristics of aviation maintainer communities, including their ETS utilization, to maintenance performance measures. We expect that as the quantity and quality of ELAR data continues to increase, greater success in this endeavor will be realized.

B. LITERATURE REVIEW

We proceed with a review of literature that addresses the analysis of aviation maintenance performance. Of particular interest to us are studies that measure the contribution of maintainers to the performance of U.S. military aviation fighting units. We begin our review with research concerned with measuring performance. We then address studies supported by the United States Air Force, an organization that faces maintenance performance issues similar to those of the Naval Aviation community. Finally, we address studies on the effectiveness of engineering and technical services.

1. Measuring Performance

One can quantify the accomplishments of aviation units in many ways: missions flown, targets struck, aircraft repaired, etc. Some of these measures are operational in nature, indicating the performance of the aircrew and their level of training, while others focus on the performance of maintenance personnel. Data elements are captured by both aircrew and technicians during and after each flight event or maintenance action, allowing analysts to calculate metrics that describe the output of the unit's maintenance effort. Commanders are also interested in their unit's ability to accomplish future missions. To this end, the Defense Department and the Services adopted metrics to quantify unit readiness. The Department of Defense Dictionary of Military and Associated Terms (Joint Publication 1-02) [CJCS, 2001] defines readiness as follows:

> **Readiness**. The ability of US military forces to fight and meet the demands of the national military strategy. Readiness is the synthesis of two distinct but interrelated levels. a. unit readiness — The ability to provide capabilities required by the combatant commanders to execute their assigned missions. This is derived from the ability of each unit to deliver the outputs for which it was designed b. joint readiness — The combatant commander's ability to integrate and synchronize ready combat and support forces to execute his or her assigned missions. [CJCS, 2001, p. 440].

The Training and Readiness Manual (T&R Manual) describes the readiness models that standardize training and readiness methodology. Navy and Marine Corps aviation decision-makers use these models to plan and budget for the appropriate number of sorties and flight hours to support unit readiness goals, which in turn places demands on resource (aircraft) readiness. At the unit level, commanders and their operational staffs use aircraft to appropriately meet training requirements.

a. Mission Capable (MC) Rates

Aviation maintenance analysts often focus on aircraft readiness rates as a primary maintenance performance indicator. Readiness is measured as an overall mission capable (MC) rate, or as not mission capable (NMC) or partially mission capable (PMC) rates. Mission capability is adversely impacted when a system or subsystem renders an aircraft incapable of performing its missions, as when components are removed from an aircraft for repair or replacement. System failures that deny mission capability are codified in the Mission-Essential Subsystem Matrices (MESM), which are available to the maintenance crews of Naval aircraft. The MESM for F/A-18 subsystems can be found in Appendix A.

As noted above, mission capability can be delineated in various ways. Fully mission capable (FMC) signifies that an aircraft can perform all of its missions. Partially mission capable (PMC) indicates that an aircraft can perform one or more—but not all—of its assigned missions. Not mission capable (NMC) implies that an aircraft can perform none of its missions, which may be further delineated as not mission capable due to maintenance (NMCM) and not mission capable due to supply (NMCS). Not mission capable due to maintenance (NMCM) is then distinguished as being due to scheduled (NMCMS) or unscheduled (NMCMU) maintenance. Each of these aspects of mission capability is used to describe a particular aircraft attached to a squadron, which is then aggregated across time to produce monthly aircraft or unit-based rates. For example, an aircraft's accrued MC time is the total time that the aircraft is in service less its NMC time. Collectively, these metrics are monitored in the Subsystem Capability and Impact Reporting (SCIR) system, which in turn provides data to the Maintenance Data System (MDS). The reader is referred to OPNAVINST 5442.4M [Chief of Naval Operations, 1990] for a detailed discussion of SCIR and MDS.

The MESM is limited to subsystems that are most likely to affect mission success and aircrew safety. As an aircraft is modified through the addition of more complex weapons, software, avionics, and even missions, commanders and maintenance managers must often deal with critical subsystems that are not explicitly listed in the MESM, which is over a decade old at the time that this thesis is written. In the absence of common standards of interpretation, individual units may introduce variability in the classification of mission capability status.

MC rates are subject to close scrutiny at all levels of command. In their testimony before the U.S. House of Representatives Committee on National Security, Steele and Dake [1998a] use MC rates to chronicle an eight-year decline in the readiness of Marine Corps warfighting units. They attribute this decline to the aging of the services' aircraft and the corresponding decrease in reliability.

b. Supply Indicators

Steele and Dake [1998a] identify a category of replacement parts, shortages of which lead to high rates of cannibalization and, consequently, increased maintenance workload, as evidenced in overlapping and rotating shifts. We infer from their reference to the increased maintenance workload the importance of metrics that quantify man-hours required to produce repairs and subsequent sorties. We discuss these in detail in Chapter II. Maintenance analysts monitor the NMCS rate to gauge the effects of the supply system on readiness. During a maintenance action, the aircraft will go through stages of repair that involve Awaiting Maintenance (AWM), Elapsed Maintenance Time (EMT), and Awaiting Parts (AWP). The time accrued in AWP status is used as another gauge of the supply system.

c. Readiness Management Tools

The Global Status of Resources and Training System (GSORTS) is a data base that was designed to provide the service branches, unified commands, and combat support agencies with the ability to monitor readiness of warfighting units. GSORTS provides the levels of selected resources and training required to undertake the mission(s) for which a unit is responsible. GSORTS consists of classified data entered by every operational unit, which they submit at monthly intervals or when dictated by other milestones such as unit deployments. Senior military officials monitor GSORTS reports to detect deviations from desired readiness trends. In their quarterly readiness report to Congress, Steele and Dake [1998b] explain how the Marine Corps uses GSORTS as a tool for monitoring readiness. They also note that readiness rates should be viewed in the proper context, since units operate on a cycle of readiness that accepts lower rates during post-deployment times when priorities shift to deploying units:

> If a unit is reporting low readiness, we first compare the unit's status in the cyclical deployment queue or, in the case of a detachment-providing unit, the number of detachments currently deployed. If these first-order cuts provide no illumination of the problem, the next step is to compare current reporting against historical trends [Steele and Dake, 1998b, p.3].

The GSORTS system categorizes readiness with respect to the following: equipment on hand, equipment condition, personnel, and training. The reporting unit assigns to each of these categories a rating that is derived from the measures of effectiveness for that category. The unit commander also provides a subjective overall rating of unit readiness known as the C-rating, in order to address intangibles not captured in numerical data.

Orlansky, Hammon, and Horowitz [1997] seek to identify reliable indicators of exercise and combat performance. Specifically, they analyze the ability of GSORTS metrics to accurately predict performance:

> Service … indicators include: personnel, training, equipment, supply, operating tempo, commitments and deployments, funding, and accident rates. Although these indicators appear likely, at least intuitively, to influence readiness, no analysis was provided to show that variations in any of them are consistently related to variations in readiness. Such work needs to be done before one should conclude that adding any of these indicators would improve our ability to evaluate current or predict future readiness. [Orlansky, 1997, p. S-3]

The authors examine the performance metrics used by the Services and compare them with measurable results from large-scale exercises, readiness evaluations, and combat. They find positive correlation between many of the currently used measures of training readiness and unit performance. Specifically, they recommend the use of those metrics shown in Figure 1 :

Table IV-1. Overview of Potential Training Readiness Indicators

Type of indicator	Indicator	Service
demonstrated training performance	percent of crews or platoons qualified	Army Marine Corps
	percent TREs above / below average	Navy subsurface
	percent of ORIs excellent or outstanding	Air Force
	percent of tasks trained to standard	Army Marine Corps
training accomplishment	percent of mission essential tasks trained	Army Marine Corps
	percent training accomplished by primary mission area	Navy
	percent of training accomplished (percent crews combat ready)	Navy aviation USMC aviation
	percent GCC level B or A	Air Force
	percent participation in CTCs/CAX	Army Marine Corps

CAX Combined Arms Exercise
CTC Combat Training Center
GCC Graduated Combat Capability
ORI Operational Readiness Inspection
TRE Training Readiness Examination

Figure 1 Potential Training Readiness Indicators [Orlansky, 1997, p. IV-2].

In addition to GSORTS, the authors consider several other sources of readiness information in their analysis, such as the Type Commander Readiness Management System (TRMS), which is a task-based readiness management system. At the time of this writing, TRMS does not incorporate measures of aviation maintenance training readiness.

Orlansky, et al. recommend that the following data-driven activity be undertaken to define the linkages between readiness and factors that may drive readiness:

1. Analyze (readiness) data to identify short term and long term trends, including noise; i.e., short-term, non-significant variations.
2. Where trends are observed, identify the time delays between inputs, i.e., resources, process, and outputs—the related consequences in …demonstrated combat capability.
3. Examine indicators for redundancy [that] add little additional information about status and trends.
4. Examine indicators that could be combined by appropriate statistical procedures.
5. Examine the relation between subjective and objective indicators of readiness.
6. Start the collection and analysis of new demonstrated performance measures. [Orlansky, 1997, p. V-2].

The authors' recommendations highlight specific areas that should be considered in cause-effect studies and that we address in our analysis: unexplained variance, lag effects, and multicollinearity, the interdependence among explanatory variables.

Orlansky, et al. cite the findings of Junor and Oi [1996], who examine all areas of GSORTS readiness, in addition to training. Junor and Oi identify 27 metrics, used by the Navy surface warfare community, that are effective in explaining or forecasting GSORTS readiness levels. In related work, Robinson, Jondrow, Junor, and Oi [1996] identify trends in Navy readiness. They use cluster analysis to divide time-series observations into discrete time intervals with minimum variability, and then employ principal components to describe the relationship between these clusters as an indication of trend. They state in their findings that readiness tends to move in long slow cycles and that GSORTS is a useful measure of readiness.

Although the studies described above do not address aviation maintenance performance metrics specifically, they provide insight into approaches and methodologies that prove useful in our analysis.

2. U.S. Air Force Studies of Maintenance Performance

The Air Force has devoted considerable effort to measuring maintenance performance and its contributing factors. Oliver [2001] examines the readiness data of U.S. Air Force F-16C/D aircraft over a ten-year period with the goal of identifying those factors that contribute to readiness. He stresses that current Air Force readiness forecasting models, while accurate, are predictive rather than explanatory models. He compiles nine years of data from aviation maintenance, personnel, and logistics sources, such as the Reliability and Maintainability Information System (REMIS), the Personnel Data System (PDS), and Manpower Data System (MDS), to derive 606 variables that may explain MC rate variability. Additionally, Oliver considers versions of each variable that are lagged by one, two, three, and four quarters, respectively, resulting in a total of 3030 variables. He then reduces the set of variables by eliminating those with low correlation to the MC rate, and redundant variables that contribute to multicollinearity. After setting aside eight quarters of data as a test set, he employs linear regression and stepwise regression to identify the smallest significant model that explains MC rates for Air Force F-16 squadrons. His final step is to build a predictive model for MC rate that includes only those variables that can be controlled by decision-makers.

Oliver recognizes that readiness is a complex phenomenon affected by many input variables:

> Most of the variables contained within each area are interrelated with one another so that changes in one variable may cause a “ripple effect” that impacts other variables [and] the research indicated that unforeseen changes in the world environment (environmental variables) created a series of powerful “ripple effects” which lead to a series of decisions that significantly influenced mission capable rates. [Oliver, 2001, p. 110]

Oliver’s study covers the ten-year period during which U.S. military fighting forces experienced a substantial decline in readiness, in large part due to downsizing after the collapse of the Soviet Union signaled the end of the Cold War. In his models Oliver attempts to control for this historical trend in order to isolate the effect on readiness due to the manning and experience levels of F-16 maintainers. He finds that manning (expressed as maintainers per aircraft) and experience (expressed as rank, skill level, or job assignment) are highly significant in explaining readiness in terms of MC rates.

In December 2001, the Air Force Logistics Management Agency (AFLMA) published *The Metrics Handbook for Maintenance Leaders* [AFLMA, 2001]. In this document, Air Force aircraft maintenance metrics are standardized, defined, and their importance explained. This handbook categorizes metrics as *leading* or *lagging* according to whether the effects that they measure occur early or late in the causal chain:

> Leading indicators are those that directly impact maintenance’s capability to provide resources to execute the mission. Lagging indicators show firmly established trends. In other words, the leading indicators will show a problem first, and the lagging indicators will follow. [AFLMA, 2001, p. 14]

MC rate is a lagging metric, as defined by AFLMA. Choosing MC rate as a response variable, as does Oliver [2001], calls for the consideration of many explanatory variables that precede the manifestation of the lagging metric. Leading metrics, such as repeat and recurrence (R/R) rates and 8-hour fix rates, however, more immediately reflect the effects of the input variables. In addition to defining performance metrics for aviation maintenance, the handbook provides insights into their effective use in the identification of trends, diagnosis of problems, and inclusion in narratives directed towards decision-makers.

Beabout [2003], who develops a visual tool to identify troublesome aircraft subsystems, also operates within the context of leading and lagging indicators. He offers techniques for separating scheduled maintenance from unscheduled maintenance activity to isolate those subsystems that cause high NMC rates.

In RAND's Project Air Force case study of an Air Force Fighter Wing, Dahlman and Thaler [2000] consider how imbalances in manning lead to shortfalls in readiness. The authors begin by describing two competing foundations of readiness: a unit's ability to respond to current operational demands of the combatant commanders and its ability to produce future capabilities through the rejuvenation of human capital:

> As units are deployed to support contingency operations, they must trade off building future capabilities for providing current ones. The longer this continues, the more units must postpone or scale back upgrade training and life-cycle maintenance of aircraft. Future commanders then have a less experienced, less capable force from which to draw. [Dahlman and Thaler, 2000, p. 2]

By acknowledging such competing requirements and the constant loss of qualified personnel from the unit, Project Air Force analysts define a 'healthy' squadron in terms of its appropriate distribution of manpower across all skill levels. Specifically, they recommend a mix of maintainer experience that will provide adequate on-the-job training (OJT) over time.

The problem is made evident by drawing analogies to the more familiar phenomenon occurring in the area of aircrew training, which ordinarily is conducted in an environment in which the number of sorties is constrained by utilization rate limits or by budget. As inexperienced pilots join the unit, and experienced pilots are transferred to other assignments, an increased percentage of the fixed number of overall available sorties must be flown by instructor pilots, leaving a smaller percentage of sorties for the junior aircrew.

The effect compounds over time, since it takes longer for those junior aircrew to meet the minimum requirements to be considered combat proficient. Dahlman and Thaler recognize the parallel problem occurring on the maintenance side:

> The dilemma emerges when experienced personnel leave at a faster rate than junior personnel can be adequately trained and promoted. … The USAF's response to diminishing retention rates largely has been to push more new personnel into critical career fields that are losing experienced personnel. This presents the wing with a "Catch-22"—it is losing experienced, productive maintainers/trainers and gaining inexperienced 3- level trainees, who require more of the experienced maintainers/trainers, whom it can generally gain only by training 3-levels. In the extreme, the additional workload can exacerbate the exodus of experienced personnel from the force, further compounding the problem. [Dahlman and Thayer, 2000, p. 13]

Other metrics gathered to support this hypothesis come from surveys of maintainers. These surveys indicate that senior maintainers spend a large portion of their workday on repair activities, as opposed to training or supervisory activities. Also significant, according to their data, is the increased time required for advancement from low ("3-level") to medium ("5-level") skill levels. The Air Force uses "3-level," "5-level," and "7-level" designations as indicators of experience.

There is a symbiotic relationship between the maintenance and operational sides of an aviation fighting unit: each must work to the benefit of the other. The aircrew need higher utilization rates from the aircraft to achieve the higher number of sorties required to train the less experienced aircrew; however, higher utilization rates on the aircraft leave less time for maintaining aircraft and for training junior maintainers, reinforcing the problems already faced by the maintenance community. Dahlman and Thaler [2000] explain how an imbalance in this relationship ultimately is felt in readiness:

> In sum, our analysis indicates a rather severe mismatch between resources available to the 388th FW and the day-to-day missions it is tasked to accomplish—namely, the requirement to rejuvenate human capital. The UTE [utilization] rates are not high enough to maintain a healthy pilot inventory. At the same time as UTE rates

> have come down, TNMCM [total not mission capable due to maintenance] and TNMCS [total not mission capable due to supply] rates have skyrocketed. Maintenance manning is becoming less experienced as junior personnel are pushed into the wing to replace a declining force of 5- and 7-levels. Although declining in number, experienced maintainers are spending more time producing sorties, overwhelming their ability to properly teach the 3-levels and to upgrade themselves, thereby threatening the long-term health of the maintainer inventory. [Dahlman and Thaler, 2000, p. 31]

Although it seems possible that Naval Aviation organizations would experience analogous concerns when faced with similar manning trends, a search of literature did not produce objective conclusions to this effect.

3. NATEC/NAESU Utilization Studies

In *NAESU Management of Technical Services*, Boynton, Seiden and Vaughan [1995] discuss Naval aviation engineering and technical services (ETS) from a management perspective: what it is that tech reps do, who needs their services, and to what level their customers are satisfied with these services. The authors begin the research by categorizing the various types of engineering and technical services from the perspectives of the tech reps and their customers, and find that there is a strong correlation between those activities deemed important by both the service providers and customers. The authors also address the significance of finding measures of performance for ETS, referencing the occasional success in identifying specific cost avoidance through the use of tech reps and the high perceived value of tech reps, yet acknowledging that no single measure has proved especially useful.

Malcolm [1995] explores NAESU technical reports (NTRs) and aircraft reliability and maintainability data to evaluate NAESU performance. NTRs document information intended to improve methods and eliminate deficiencies. Malcolm defines cost savings as a performance measure, and proposes that NTRs can be studied to derive the cost savings associated with the implementation of the tech rep recommendations. After analyzing several hundred NTRs over a twenty year period, he concludes that an individual NTR can be used to derive these cost savings. Malcolm acknowledges the difficulty in isolating the affects of NTRs, noting that sources of information other than NTRs also impact the change process.

Boynton et al. [1998] continue previous studies and further develop organizational measures of effectiveness for NAESU. They conclude that accepted measures of industrial productivity are not appropriate measures of effectiveness of tech rep activities, primarily because tech rep “output” is not defined in quantifiable terms:

> …it would seem that measures of economy and measures of effectiveness could be developed for NAESU. Measures of productivity, however, would be very difficult and arbitrary. Production units of input and output, required to develop input/output ratios, are not definable in this kind of intangible, knowledge-intensive environment. [Boynton, 1998, p. 20]

Instead, the authors focus on client satisfaction, economic impact, and contribution to NAESU organizational objectives. The authors note that cost savings realized by tech rep activity is enjoyed not by NAESU/NATEC but instead by the client customer. They also note the difficulty in isolating the tech reps’ contributions from other factors that affect readiness. The authors dismiss what may seem to be the obvious means of measuring tech rep effectiveness—a controlled experiment in which such services are available to some squadrons and not others—due to the predictable objections raised by units that would be adversely affected by such an experiment. Instead, they recommend the development of a periodically administered random survey that addresses broad categories of training, liaison, advice, and maintenance, across all customer categories, to identify indicators of service quality.

4. Measuring the Value of Human Capital

Senior maintenance personnel and tech reps are noteworthy in that they have years of experience to draw upon when training less experienced maintainers and when troubleshooting aircraft problems. Much of their value, therefore, lies in what industry refers to as "intellectual capital", an important but difficult asset to quantify. Wagner [1998] leverages industry techniques to assess the purported loss of intellectual capital attributed to the drawdown of U.S. Air Force line officers from 1989 to 1997. He proposes to first measure human capital and then match the Air Force's intellectual needs with its strategic plan. Wagner uses measure of human intellectual capital that are analogous to those used in industry: education, experience, stability, growth, and efficiency. He concludes that increased trends in these measures suggest that although overall numbers of Air Force line officers decreased between 1989 and 1997, the Air Force managed their intellectual capital effectively.

C. FOCUS OF THE THESIS

The primary objective of this thesis is to identify squadron characteristics that are important predictors of maintenance performance. In other words, we want to determine which characteristics differentiate the squadrons with respect to a given performance parameter. We hope that the process will serve as proof of concept and can be used as a tool to include other squadron characteristics as data becomes available. A secondary objective is to draw insights regarding the utility of data currently being collected by NATEC and to make recommendations for improvement if appropriate. Specifically, we want to answer the following research questions:

1. Which squadron characteristics have a detectable contribution to the variability of the performance measure *man-hours per maintenance action*?

2. How much additional variability is explained by the squadron that is not accounted for by the squadron characteristics already considered?

3. Is there a time-of-year effect for the performance of the squadrons?

4. What additional metrics not currently available would most likely be useful in an explanatory model of maintenance performance?

5. What data collection methods, if any, would be likely to improve the ability of NATEC managers to correlate squadron characteristics to tech rep measures of performance?

We address the first three questions in Chapter III, and the last two questions in Chapter IV.

D. SCOPE OF RESEARCH

We address our research objectives as they pertain to Marine Corps squadrons that operate the F/A-18, a multi-role strike fighter flown in both the Navy and Marine Corps. Since the Navy and Marine Corps differ somewhat in their missions, operational cycles, and other factors, we control for the "service effect" by focusing on Marine Corps squadrons. Similarly, differences found in reserve and training squadrons are controlled by considering only active duty fleet squadrons. The current Marine Corps inventory consists of thirteen active duty F/A-18 squadrons of aircraft model types A, C, and D that are included in this analysis.

Figure 2 Marine Corps F/A-18 Fighter Attack Aircraft.
F/A-18 aircraft such as that pictured here are operated by squadrons stationed at Marine Corps Air Station (MCAS) Miramar, CA and MCAS Beaufort, SC. VMFA-212 is permanently assigned to MCAS Iwakuni, Japan.

Although tech reps interact with maintenance personnel at both the intermediate level and organizational (squadron) level, we limit our analysis to organizational level (O-level) maintenance. Finally, since NATEC has documented the activity of its tech reps in ELAR since August 2003, analysis that includes tech rep variables is limited to the time window August 2003 to May 2005. Data pertaining to variables other than tech rep activities encompasses, at a minimum, this time period.

E. ORGANIZATION

Chapter II describes the objective and methodology used in the collection of data to support the analysis. After defining the metrics that describe the squadrons' characteristics, we identify the sources of the data that allow us to derive these metrics. Chapter III begins with an exploration of the data as time series plots. After eliminating redundant variables we employ regression analysis techniques to identify those characteristics that are related to performance. Chapter IV summarizes the work and makes recommendations for further study.

II. DATA COLLECTION

A. OBJECTIVES

The purpose of this thesis is to identify squadron characteristics that can explain the performance of its maintenance crew. The data collection effort supported our analysis by focusing on data elements that describe the squadron characteristics in quantifiable terms, and which describe the performance output of a squadron's maintenance department.

Our goal is to express the various characteristics of the squadrons in terms of personnel makeup, aircraft inventory, maintenance activity, and operational activity. In this respect we are describing *what* the squadrons are doing, *who* they're doing it with, and *what* they're doing it with. We want to quantify performance in terms of mission capability rates, times to repair, and the frequency of certain types of repair. Low capability rates may signify that the squadron is not getting sufficient flight hours from the aircraft in its possession. Long times to repair may indicate poor maintenance management, slow aircraft turnaround activities, or even a lack of personnel capabilities. High frequency of repair may be more indicative of a reliability problem than of a maintenance problem, so we limited our scope to those types of repair that are indicative of maintenance performance. Finally, we need to consider these factors in the context of changing operational tempo and deployments, so we obtained data that describe squadrons in operational terms as well.

B. METHODOLOGY

We began the data collection effort by identifying metrics that capture the squadron characteristics that we want to quantify. With these metrics in mind, we identified data sources that contain these metrics (or the raw data that allow them to be derived) for the squadrons under consideration in this study. From each of these sources, we collected time series data encompassing, at a minimum, the period August 2003 through May 2005. Since each of the data sources provides data at differing levels of detail, we decided on a time unit that facilitates a useful, common level of aggregation. Many available metrics were already aggregated on a monthly basis, so further decomposition to a weekly or daily interval was avoided. The data also needed to be aggregated to the appropriate organizational level. Although some detailed metrics attribute maintenance activity to a single aircraft, the squadron is the smallest maintenance organization to which all our metrics apply. The data were aggregated to the squadron level and filtered to include only the following squadrons:

Third Marine Aircraft Wing Marine Aircraft Group 11 Marine Corps Air Station Miramar, CA	Second Marine Aircraft Wing Marine Aircraft Group 31 Marine Corps Air Station Beaufort, SC
VMFA-232	VMFA-115
VMFA-314	VMFA-122
VMFA-323	VMFA-251
VMFA(AW)-121	VMFA-312
VMFA(AW)-225	VMFA(AW)-224
VMFA(AW)-242	VMFA(AW)-332
	VMFA(AW)-533

Table 1. CONUS-Based Active Duty Marine F/A-18 Squadrons

For data elements that are measured over a large number of individuals or aircraft in a given month, we use summary statistics such as quartiles to condense the data into single values per squadron per month. Each metric, therefore, takes the form $X_{s,t}$, where s represents the squadron and t represents the month. For certain metrics we are constrained by the months for which data was not collected or made available to us. Since we are analyzing a collection of factors across a consistent timeframe, we limited our data collection effort to a time frame that was common to each.

C. METRICS AND THEIR SOURCES

We identify sources of data that allow us to develop a set of metrics that quantify the characteristics of the squadrons in terms of operational activity, maintenance activity, personnel makeup, and aircraft inventory. These data sources are not linked and are not designed to share data or commonality of data format. As such, we develop metrics that can be brought together on a common scale or time increment. Each metric is categorized by its relation to operations, maintenance, personnel composition, or aircraft inventory.

1. Flight Operations and Maintenance Metrics

Flight operations metrics are characterized by their relationship to the daily flight schedule. We expect the volume of maintenance activity to vary with the demands of flight operations. Although operational demands may be beyond the control of the maintenance department, we use operational metrics to normalize maintenance statistics to a common scale.

We accessed the Navy's Maintenance Data System (MDS) to collect the data elements used to describe maintenance and performance and flight operations. MDS, managed by Naval Air Systems Command (NAVAIR), is a management information system designed to provide statistical data on equipment maintainability and reliability, configuration, mission capability and utilization, material usage and non-availability, and maintenance and material processing times and costing. Maintainers and aircrew input data into MDS using the Naval Aviation Logistics Command Information System (NALCOMIS), the primary maintenance interface that integrates all maintenance functions and allows managers to visualize critical maintenance trends through pre-designed or customizable reports. For access to data maintained in NALCOMIS, we used the web-based Decision Knowledge Programming for Logistics Analysis and Technical Evaluation (DECKPLATE), which provides report and query capabilities of Naval Aviation logistics and flight event data to compile the maintenance and operational characteristics of each squadron. For each of the metrics described previously, we collected data for the period October 2002 to April 2005.

From these data sources, we identify operational and maintenance metrics that allow us to quantify performance output in measurable terms. We group the operational metrics as measures of utilization and operational tempo, and group the maintenance metrics as measures of maintainability and reliability.

a. Measures of Utilization

Each squadron operates its aircraft at rates required for training or for contingency operations. We anticipated the need to control for these factors and therefore collected measures of utilization: *flights*, *flight hours*, *utilization*, and *deployment status*.

Flights* and *Flight Hours. These metrics are, respectively, the total number of flights and flight hours flown by the entire squadron during the designated time period. The flights metric is reported as an integer value, and the flight hours metric is reported to the nearest tenth of an hour. We categorize both flights and flight hours as performance metrics.

Utilization. The *utilization* metric is the average number of hours flown per aircraft during a given month, and is reported to the nearest tenth of an hour. We categorize this metric as a performance metric.

b. Measures of Operational Tempo

Arguably, squadrons that are deployed or approaching their deployment date experience higher supply prioritization, better support equipment, personnel augmentation, boosted morale, and a higher sense of urgency. The metric *deployment status* attempts to capture these factors. This categorical metric distinguishes between the following deployment modalities:

- Continental U.S. (CONUS)
- Unit Deployment Program (UDP)
- U.S. Navy aircraft carrier (CVN)
- Combat contingencies, which during the time frame of this thesis consisted either of Operation Enduring Freedom or Operation Iraqi Freedom.

To collect the data that would allow us to categorize the *deployment status* of the squadrons, we turned to various unclassified, publicly accessible sources of squadron historical records such as press releases [Pasnik, 2005], official squadron web sites and widely-used military synopsis web sites [GlobalSecurity.org, 2005]. Use of *deployment status* in our analyses allows us to control for the operational tempo of a squadron when we compare its performance metrics to those of other squadrons. We categorize *deployment status* as an operational metric.

c. Measures of Availability

An important descriptor of maintenance performance is the proportion of aircraft not available for operations or training. This measure can be delineated by the specific reason the aircraft is not available for training – ongoing corrective or preventative maintenance, or supply delays.

Not Mission Capable–Maintenance (NMCM) rate*.* *NMCM* is the proportion of total reported time that a squadron's aircraft are not mission capable due to maintenance actions required. Low *NMCM* rates are desirable, whereas high *NMCM* rates may indicate poor maintenance management, capabilities, prioritization, or flight operations coordination practices. *NMCM* rates can be further delineated by non-mission capability resulting from scheduled maintenance (*NMCMS*) and unscheduled maintenance (*NMCMU*). Scheduled maintenance can be planned and managed by effective maintenance managers. Unscheduled maintenance results from unanticipated breaks. We categorize this family of mission-capability measures as performance metrics.

Not Mission Capable–Supply (NMCS) rate. *NMCS* is the proportion of total possessed time that the squadron's aircraft are not mission capable due to supply reasons. Although some of this time is attributable to supply shortages, this metric can also be influenced by maintenance practices. Maintenance analysts can identify which parts are responsible for putting an aircraft in an *NMCS* status. Some parts are well known for being on long back-orders, while others, although usually available, are frequently ordered. We categorize *NMCS* as a performance metric.

d. Measures of Maintainability

Man Hours per Flight Hour. This metric provides an indication of the amount of maintenance effort associated with each flight hour flown by the squadron. A large value of *Man Hours per Flight Hour* may be associated with older, less reliable aircraft that require additional maintenance, or perhaps an indication of a less capable manpower base. We categorize this metric as a performance metric.

Man Hours per Maintenance Action. This metric quantifies the average number of man hours required to complete a maintenance action, and is calculated by dividing the total number of man hours by the number of maintenance actions for each of the 31 months in the data query. Since many maintenance actions result from normal equipment failure, while others are operationally driven (in that they are triggered by accumulated flight hours), the number of maintenance actions is driven largely by circumstances beyond the control of the maintenance department. The number of maintenance actions, therefore, is not by itself a good indicator of the health of the maintenance department. Instead, we use this number as a scaling factor to normalize other measures, such as maintenance man hours, to a common scale, which we quantify as *Man Hours per Maintenance Action*. We categorize this metric as a performance metric.

TD Hours. On occasion, squadrons are instructed to incorporate changes, such as airframe modifications and avionics upgrades, to the aircraft in their possession. These changes are known as technical directives (TDs). *TD hours* quantifies the amount of time dedicated by a squadron to address the changes required by TDs. We separate out this type of maintenance activity because it may require additional expertise or perhaps external support. Perhaps squadrons with higher overall capability levels will accomplish TDs in shorter amounts of time. *TD hours* is quantified in units of hours for a specified squadron and month. We categorize *TD hours* as a performance metric.

To collect the *TD hours* metric we accessed the Technical Directive Status Accounting (TDSA) database and collected 25 months of data from April 2003 to April 2005. This metric is reported in hours to the nearest tenth.

e. Measures of Reliability

Metrics that quantify the frequency of repair are often used to evaluate system reliability. Instead, we limited our use of repair-frequency metrics to those that characterize maintenance performance rather than aircraft reliability.

Cannibalizations per 100 hrs*.* This metric is the average number of cannibalizations per 100 hours. A cannibalization is the removal of a serviceable part from an aircraft to replace an unserviceable part of another aircraft. Curtin [2001] testifies to Congress the effects of cannibalizations:

> Cannibalizations have several adverse impacts. They increase maintenance costs by increasing workloads, may affect morale and the retention of personnel, and sometimes result in the unavailability of expensive aircraft for long periods of time. Cannibalizations can also create unnecessary mechanical problems for maintenance personnel. [Curtin, 2001, p. 2].

Since cannibalizations occur when the required parts are not immediately available from the supply system, this metric is often used as a measure of supply effectiveness. A rising value usually results in an increase in the number of man-hours required to achieve the same *utilization* rates and *flight hours* and risks causing additional problems to the cannibalized aircraft. We categorize this metric as a performance metric.

A799s per Flight Hour. This measure quantifies the frequency of circumstances where maintenance personnel are unable to diagnose a problem that was identified by the aircrew. Such cases are documented in NALCOMIS with the Maintenance Action Code A799, which signifies that the maintenance personnel could find no defect and took no corrective action. In some cases, this represents a failure on the part of maintainers to resolve a problem. In other cases, it represents a failure on the part of the aircrew to appropriately describe the problem, or simply the reality that environmental conditions in the repair facility are not the same as those under which the failure occurred. We categorize this metric as a performance metric.

2. Personnel Metrics

The maintenance organization of a squadron is staffed to handle most of the squadron's maintenance requirements. The ability of a squadron to meet operational demands lies largely with the capabilities of the maintenance personnel. We attempt to quantify their capability with a variety of personnel metrics that may characterize capability to some degree. We develop personnel metrics with enough variability to help explain differences in maintenance performance on a monthly basis. Manpower metrics that may prove useful in quantifying a unit's capabilities are those that capture the maintainers' collective experience level, as measured by their years or months of service or their time in the current squadron. These variables, while not direct measurements of individual capability, may serve as useful representatives for such a measure. In addition to these measures of experience, we express a unit's capability with measures of stability.

The personnel metrics we use in the analysis were derived from records extracted from the Marine Corps Total Force System (MCTFS). MCTFS is the single, integrated, personnel and pay system supporting both Active and Reserve components of the Marine Corps. To derive the desired metrics, we created monthly squadron personnel snapshots for a 24-month period beginning May 2003. We compiled the records of those personnel that were members of the designated squadrons during each of those months. In addition to each individual's name and unit, we collected the following data from MCTFS to allow for calculation of desired metrics:

- Military Occupational Specialty (MOS).
- Date arrived at current duty station (ArrPermDutySta)
- Date departed previous duty station (DepPermDutySta)
- Rank (grade).
- Months served on active duty (Active Service).

a. Measures of Experience

We express the capability of a squadron, to a certain extent, in terms of the collective experience of the maintenance personnel.

Months in Service (lower quartile, median, upper quartile). These three metrics quantify the distribution of experience of the maintainers, using time in service as a measure of experience. The lower quartile, or 25th percentile, is the value such that approximately one-quarter of the sample lies below it. The upper quartile, or 75th percentile, is the value such that approximately one-quarter of the sample lies above it. About half of the sample, therefore, lies between the lower and upper quartiles. The median, or 50th percentile, is the value such that about half of the sample lies below and half of the sample lies above that value. A Marine Corps F/A-18 squadron is assigned approximately 150 maintainers, but the actual number of maintainers in a given squadron fluctuates somewhat, especially during the months preceding or immediately following a deployment. We aggregate the monthly data of the individual maintainers into quartiles to preserve some information about the distribution of experience in the squadron, resulting in three metrics for each squadron per month. The unit of measure for this metric is months. We categorize this metric as a descriptive metric.

Months in Squadron (lower quartile, median, upper quartile). These three metrics quantify the distribution of experience of the maintainers in terms of their time in their current squadron. We recognize that individuals' time in the service may be interrupted by duties unrelated to maintenance work. This metric eliminates periods of interruption by considering only the time spent in a particular squadron. As with the *months in service* metrics, we aggregate the monthly data of the individual maintainers into quartiles, resulting in three separate metrics. The unit of measure for this metric is months. We categorize this metric as a descriptive metric.

b. Measures of Stability

The personnel that comprise the squadrons' maintenance organizations change on a daily basis. We characterize manning stability by the frequency, magnitude, and trends of these personnel changes.

Turnover rate. This metric expresses stability in terms of the number of individuals entering and leaving the organization as a proportion of the total number of individuals in the organization. We categorize this metric as a descriptive metric.

3. Aircraft Inventory Metrics

Although each squadron is assigned twelve F/A-18 aircraft, the type/model/series of these aircraft differ between squadrons, as do their accrued use and age. To develop the metrics needed to describe inventory characteristics, we obtained monthly reports from NAVAIR which were compilations of data extracted from the Aircraft Inventory Readiness and Reporting System (AIRRS) and SAFE [Kaitchuk, R., personal email correspondence, July 10, 2005]. AIRRS provides on-line access to aircraft inventory, readiness, and flight utilization data. SAFE is the structural appraisal of fatigue effects. Output from AIRRS was made available to us in a series of files, each of which was a monthly snapshot of inventory data. Since each squadron operates multiple aircraft, we used the mean to represent the distribution of each squadron's inventory metrics for a given month. The following metrics are used to quantify these inventory characteristics.

Type Equipment Code (TEC). Each squadron operates a single type/model/series of aircraft. Varying aircraft types may demand different maintenance efforts, so we categorize them appropriately. TEC categorizes the aircraft type with a four-letter code; the F/A-18A, F/A-18C, and F/A-18D are represented by the codes "AMAA," "AMAF," and "AMAG," respectively. We categorize this metric as a descriptive metric.

Airframe Hours. This metric indicates the accrued flight hours that have been accumulated over the life of the aircraft during its lifetime, averaged across the inventory of aircraft.

Airframe Months in Service. This field indicates the total number of months that each aircraft in the squadron has been in operation since entering service.

4. Engineering and Technical Support (ETS) Metrics

As described in the Background section, ETS support is provided by tech reps that are available to each squadron. NATEC uses the ELAR database to track initiated requests for ETS assistance through execution and completion. ELAR records date back to August 2003. We collected all records available, filtered to include only those associated with F/A-18 organizations, and developed metrics that allow us to include the frequency of these support assists in our analysis.

***Records per Month*.** This metric quantifies the volume of ETS activity by quantifying the number of assists provided to the squadrons. We categorize this metric as a descriptive metric.

5. Location and Organization.

Although we want to identify underlying causes that result in performance variation, we might find that performance is explained in part by *location* and factors associated with different operating bases, such as the variety of support structures or local policies not otherwise identified in this analysis. Table 1. lists the squadrons and their associated home bases. Since only two bases are associated with the squadrons under investigation, we can use a two-level factor to identify the observation as either "Beaufort" or "Miramar."

We are trying to explain variability in squadron performance by quantifying the inherent characteristics of the units with metrics that are applicable to all squadrons. However, we have to consider the possibility that some of the variance is described by other variables not yet considered. A categorical variable indicating the squadron, called *organization*, will be used to capture additional variance due to squadron differences that are not captured by the operational, personnel or inventory variables described in this chapter. We should note that when using *organization* as an indicator, we identify *location* and *type equipment code (TEC)* implicitly, since *organization* uniquely identifies its *location* and *TEC*.

D. COMPILATION OF DATA

Table 2. summarizes the metrics and the sources of data that we used to derive them.

Data Source	**Group**	**Metric**	**Type**
NALCOMIS	Measures of Utilization	Flights and Flight Hours	Performance
		Utilization	Performance
	Measures of Availability	NMCM	Performance
		NMCS	Performance
	Measures of Maintainability	Man-hours per flight hour	Performance
		Man-hours per maintenance action	Performance
		TD hours	Performance
	Measures of Reliability	Cannibalizations per flight hour	Performance
		A799s per flight hour	Performance
MCTFS	Measures of Experience	Months in service quartiles	Descriptive
		Months in squadron quartiles	Descriptive
	Measure of Stability	Turnover rate	Descriptive
AIRRS	Aircraft Type	Type equipment code	Descriptive
	Measures of Aircraft Age	Airframe hours	Descriptive
		Airframe months in service	Descriptive
ELAR	Measure of ETS Activity	Records per month	Descriptive
Various	Measure of Ops Tempo	Deployment Status	Descriptive
N/A	Measure of Environment	Location	Descriptive

Table 2. Groups, Types and Sources of Metrics

The number of observations n is determined by the number of months (31) multiplied by the number of squadrons under investigation (13) for a total of n = 403 observations of the form $X_{i,s,t}$, where i = variable number, s = squadron, and t = month. For ease of manipulation we arranged the observations in a table of n observations (rows) of 24 variables (columns). Some of the observations contain missing values for certain variables. Only 209 observations have no missing values. A portion of the table is shown in Appendix C.

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III. ANALYSIS

A. OBJECTIVE

The objective of the analysis phase is to describe, in mathematical terms, the relationship between active component Marine Corps F/A-18 squadrons' descriptive metrics and their performance metrics, which we define in Chapter II.

B. APPROACH

We begin by analyzing trends and variability of the performance and descriptive metrics with the use of time series plots and histograms. An understanding of trends and patterns provides insights to where measurable differences between squadrons may exist, and where there is correlation between factors. After discussing the performance metrics, we focus on a single performance metric, *man-hours per maintenance action,* for further analysis. Through the use of correlation analysis, we limit the complexity of the model-building problem by reducing the set of potential predictor variables to a smaller representative subset. We then direct our analysis to answer the following research questions:

1. Which squadron characteristics have a detectable contribution to the variability of the performance measure *man-hours per maintenance action*?

2. How much additional variability is explained by the squadron that is not accounted for by the squadron characteristics already considered?

3. Is there a delayed response (lag) between any of the descriptive (predictor) variables and the performance measure (response) variable?

4. Is there a time-of-year effect for the performance of the squadrons?

To answer the first question, we use predictor variables and a response variable in regression analysis to construct a linear combination of descriptive variables that best explains the variability of the squadrons' performance. To answer the second question, we add the categorical variable *organization* to the resulting model, to determine whether the predictive power of the model is increased; and if so, to what extent.

C. TIME SERIES EXPLORATION

1. Performance Measures

We begin by identifying those metrics that best describe maintenance performance. Although we have access to numerous metrics that measure maintenance activity, many of them simply count system failures or maintenance actions and their frequency. As such, they are measures of reliability rather than of maintenance performance, designed to identify to supply-chain analysts those critical components that may be exhibiting high rates of failure. These higher failure rates could be a result of factors that do not reflect maintainer capability. Instead, we focus on those metrics that quantify capabilities of the personnel performing the repairs once the failures have occurred. We will limit our initial analysis to the following performance metrics as response variables: *not mission capable due to maintenance, unscheduled (NMCMU), man hours per flight hour*, *man hours per maintenance action*, *A799 actions per flight hour*, and *cannibalization actions per flight hour*. After describing the distributions and variability of these five response variables, we will use *Man Hours per Maintenance Action* for more rigorous analysis – as a case study and proof of concept for addressing the objectives and primary research questions posed in Chapter I.

a. Not Mission Capable Due to Maintenance, Unscheduled (NMCMU)

NMCM is the proportion of total Equipment in Service (EIS) time that an aircraft is not fully mission-capable due to ongoing maintenance activity. NMCMU is more narrowly defined by maintenance of the unscheduled variety. Figure 3 depicts the monthly movement of this metric for the thirteen active duty Marine Corps F/A-18 squadrons. NMCMU ranges from 0 to 0.3, with an average value of 0.12, across the squadrons and timeframe considered.

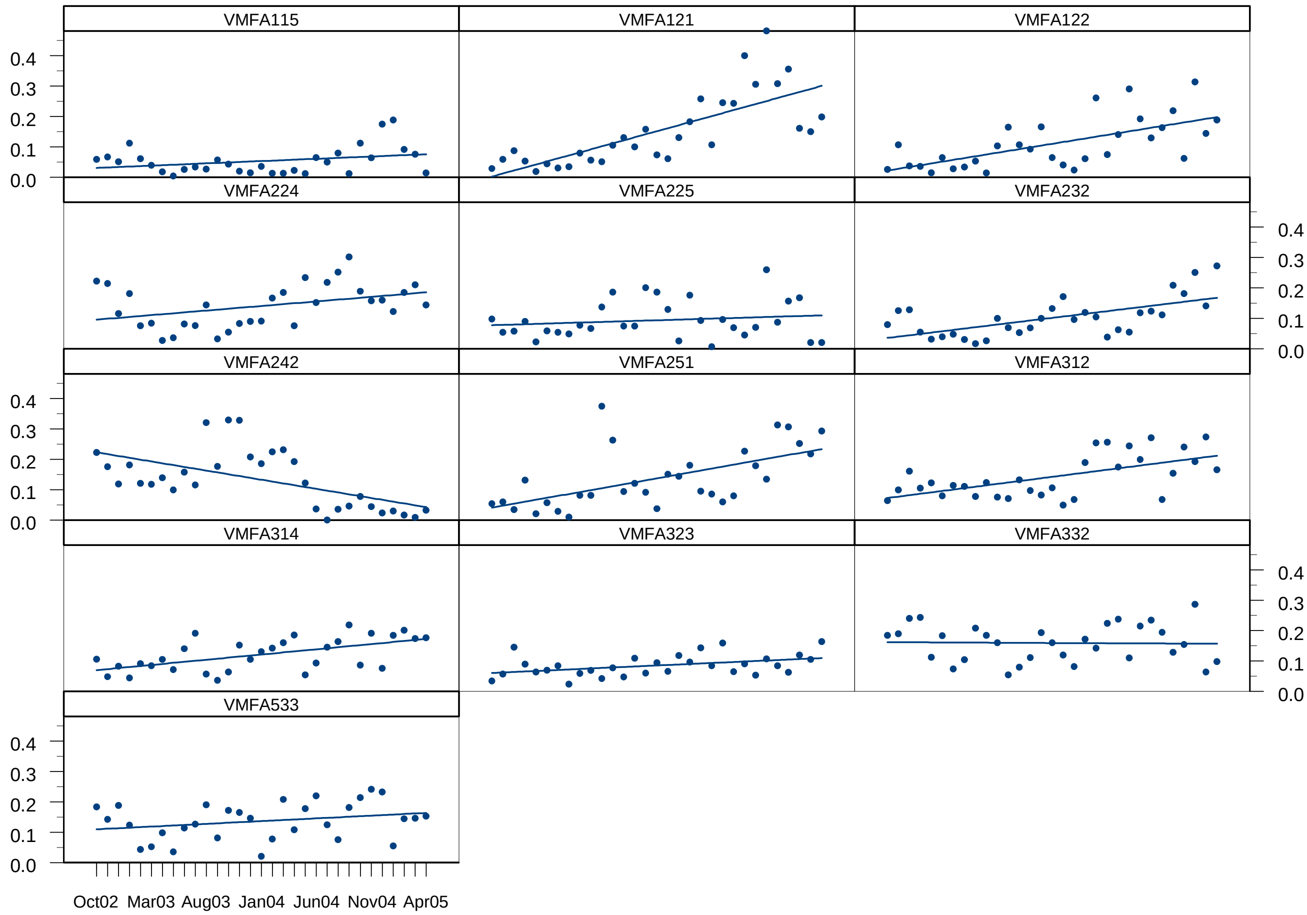

Figure 3 NMCMU Time Series for Active Duty Marine Corps F/A-18 Squadrons.
Each panel represents 31 months of data for each squadron. Squadron labels appear above each time series plot. NMCMU is expressed as a proportion on a scale from 0 to 1.

Figure 3 indicates that there is variability in NMCMU both within squadrons and between squadrons. In some units, such as VMFA121 and VMFA251, we see upward movement of NMCMU for the months between October 2002 and April 2005, which is not a desirable trend. VMFA242, on the other hand, exhibits a decreasing trend. The graph does not indicate obvious dependence between squadrons, but more rigorous tests for correlation will be conducted later in this chapter.

b. Man Hours per Flight Hour and Man Hours per Maintenance Action

The *man hours per flight hour* metric is calculated by dividing the total maintenance man hours in a given month by the flight hours flown in that same period. We expect a squadron that flies more flight hours to experience higher demands for both corrective and preventative maintenance. By normalizing the man-hour data with the number of flight hours, we control for the tendency of failures, maintenance actions, and therefore man-hours, to increase with flight hours. In this way we hope to isolate personnel capability from reliability factors. A problem with the use of flight hours as a scaling factor arises when extremely low values of flight hours destabilize those metrics with flight hours in the denominator. If we use *maintenance actions* rather than *flight hours* to normalize the man hours data, we quantify the average number of man hours it takes the squadron to complete each maintenance action and isolate maintenance activity from an operational factor. An added benefit of scaling with maintenance actions is that we do not see extremely low values in the denominator of the *man hours per maintenance action* ratio. Figure 4 depicts the movement of *man-hours per flight hour* and *man-hours per maintenance action* on the same time series plot.

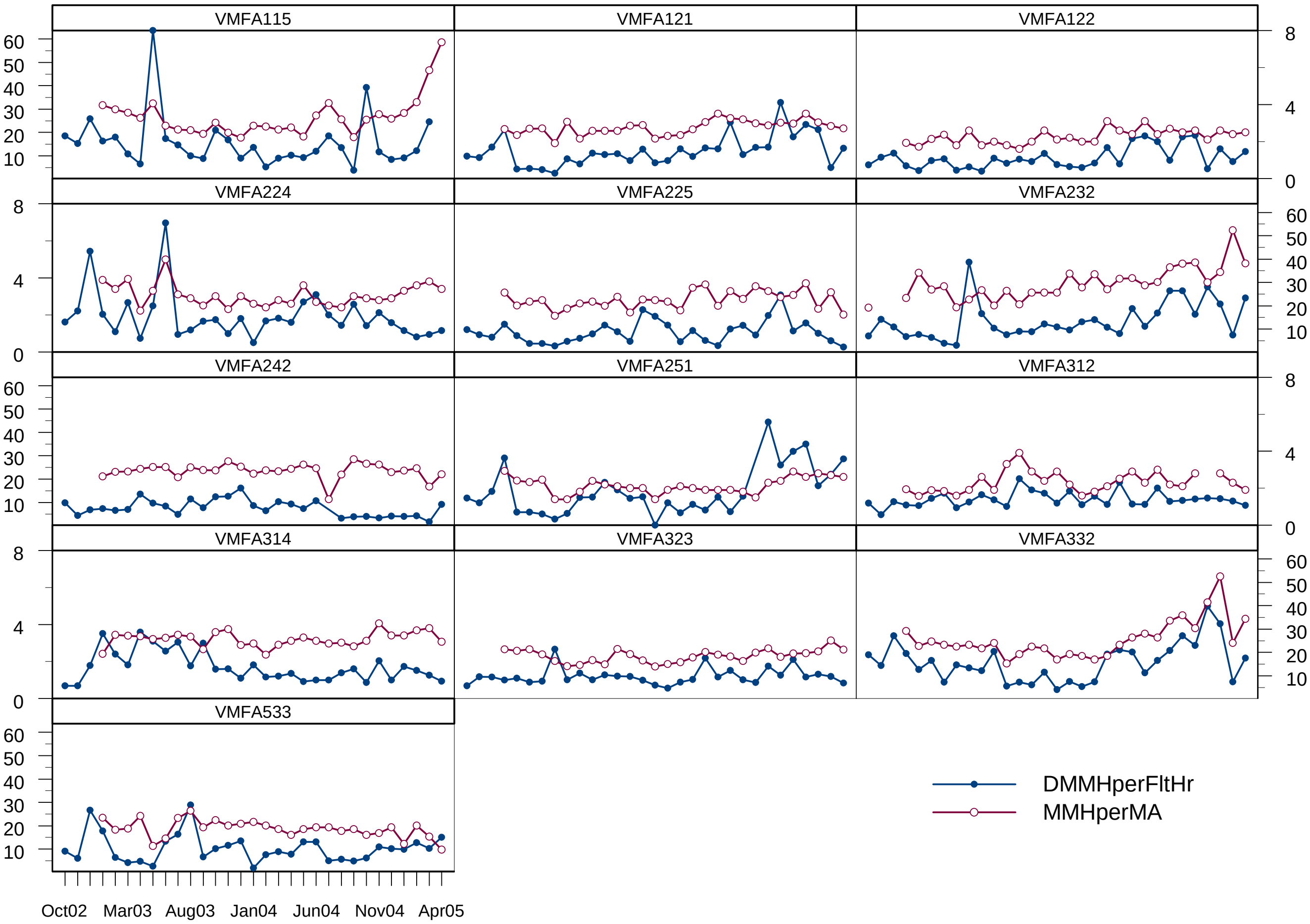

Figure 4 **Man-Hours per Flight Hour and Man Hours per Maintenance Action Time Series by Squadron.**
Each panel shows 31 months of data for man-hours per flight hour and man-hours per maintenance action. Those months with fewer than 50 flight hours have been omitted, since they tend to distort the effects of data normalized by flight hours.

Similar movement between the time series plots of Figure 4 indicates that *man-hours per maintenance action* and *man-hours per plight hour* may be correlated metrics, and our choice of which is more suitable as a performance measure may depend on a more nuanced understanding of how they are derived. Values of *man-hours per flight hour* range from 0 to 34.8, with a mean of 7.02. Lower values of this metric suggest a more efficient work force, perhaps a result of more experienced or better trained personnel. Some of the squadrons, such as VMFA332 and VMFA232, appear to exhibit increasing values in these two performance metrics, which is an undesirable trend. Other squadrons, such as VMFA224, had individual months during which the man-hours metrics were remarkably higher than average. In the next section, we will attempt to identify those squadron characteristics that explain the monthly variability and long-term trending of the *man-hours per maintenance action* metric.

c. A799s per Flight Hour

As described in Chapter II, A799s are maintenance actions in which the maintainers could not identify the problem and took no further action. If a malfunction reported by aircrew is not identified or duplicated by maintenance personnel, the aircraft may be determined to be safe for flight and the action marked complete with an A799 code. In some cases, this represents a failure on the part of maintainers to resolve a problem, while at other times the error lies with the aircrew in poor communication or misdiagnosis of the problem. Figure 5 depicts the movement of this metric over time within squadrons and their corresponding least-squares trend lines.

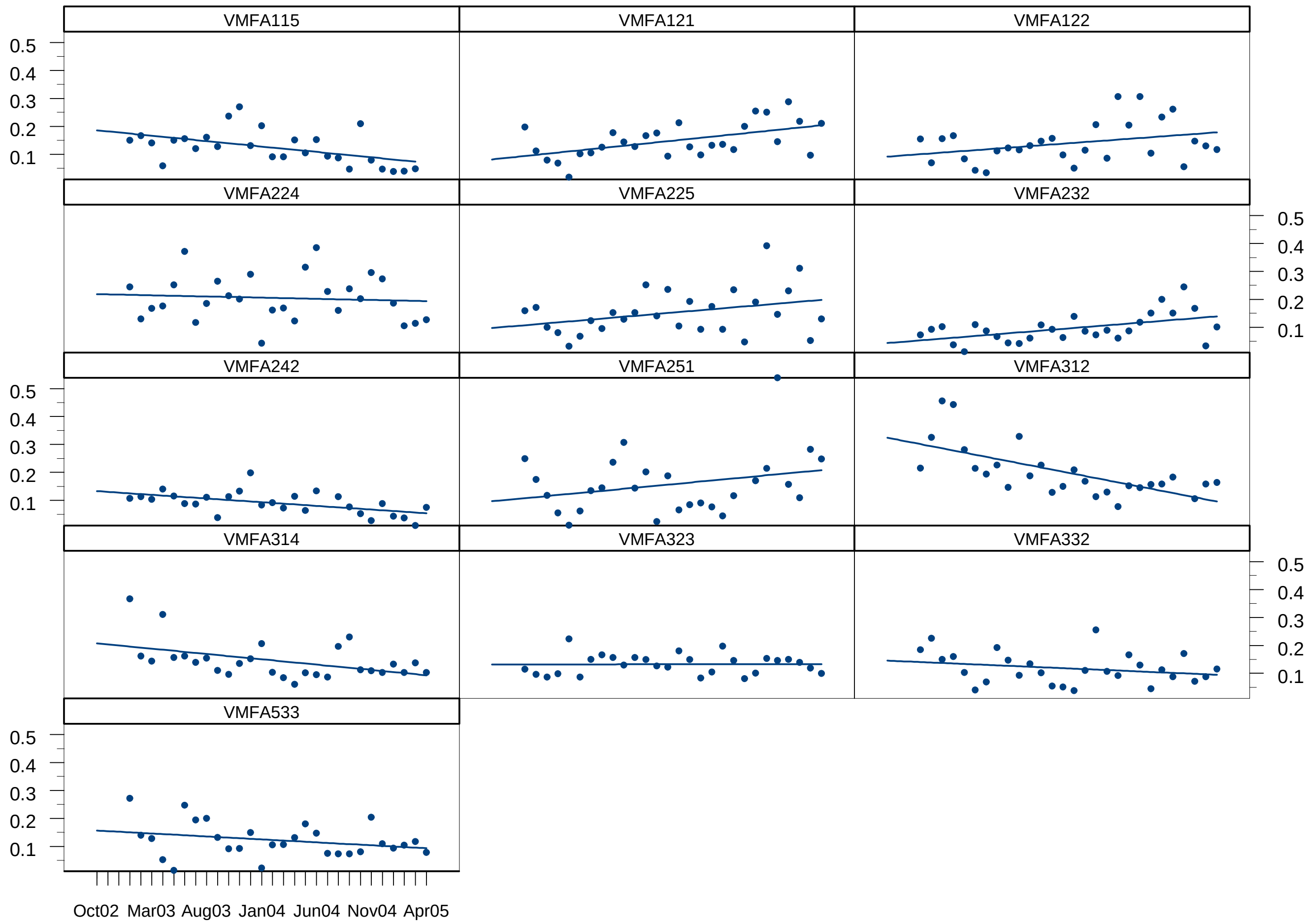

Figure 5 A799 Maintenance Actions per Flight Hour Time Series for Active Duty Marine Corps Squadrons.
Each panel represents 28 months of data from January 2003 to April 2005. Months during which squadrons flew fewer than 50 flight hours have been omitted.

Most squadrons exhibit noticeable variability with respect to this metric. Some squadrons, such as VMFA121, 122, 225, 232 and 251 show increasing values of this metric, which is an undesirable trend. Others, such as VMFA312, show a movement in the desired direction. There is no single obvious characteristic that differentiates these particular squadrons, which immediately highlights the need for more techniques that can consider multiple variables.

d. Cannibalizations per Flight Hour

Another metric that may provide an indication of maintenance performance is the cannibalization rate, expressed as *cannibalizations per flight hour*. Squadrons strive for lower values of this indicator, since higher values reflect a less-responsive supply system and an increase in the man-hours required to achieve a desired level of output (flight hours, mission capable aircraft, etc). Figure 6 depicts the *cannibalizations per flight hour* time series with least-squares trend lines superimposed.

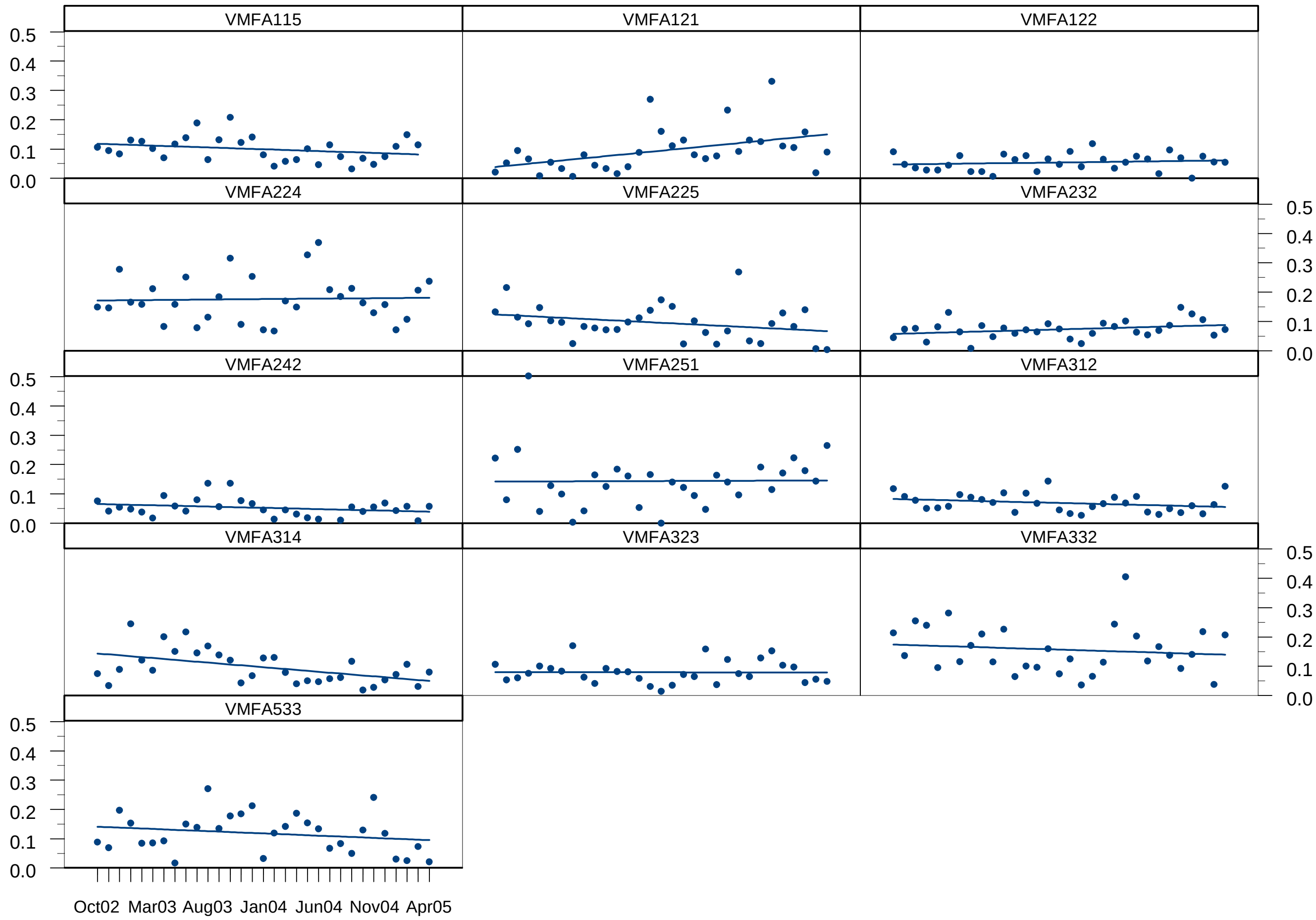

Figure 6 Cannibalizations per Flight Hour Time Series for Active Duty Marine Corps F/A-18 Squadrons
Each panel represents 31 months of observations for a given squadron. Least-squares trend lines are superimposed on each squadron's time series.

VMFA121 shows upward movement in the *cannibalizations per flight hour* metric, which is an undesirable trend, whereas VMFA314 shows desirable downward trending. High values of this metric may reflect supply shortfalls, lower personnel experience levels, training deficiencies, or mismanagement of resources.

e. Technical Directive (TD) Hours

As described in Chapter II, TD's are specialized maintenance actions, directed by Naval Air Systems Command (NAVAIR), which can be of an immediate or less urgent nature. Squadrons are obligated to incorporate those TDs that affect flight safety by performing immediate, dedicated repairs, but squadrons tend to address those of a less urgent nature when the aircraft are undergoing other preventive or corrective maintenance. Some squadrons may classify TDs as unscheduled maintenance and will therefore accrue NMCMU time [reference Chris Hawes email]. To the extent that this is the case, TDs may be correlated with the NMCMU metric. Figure 7 overlays the hours required to incorporate these TDs and the NMCMU metric on one plot.

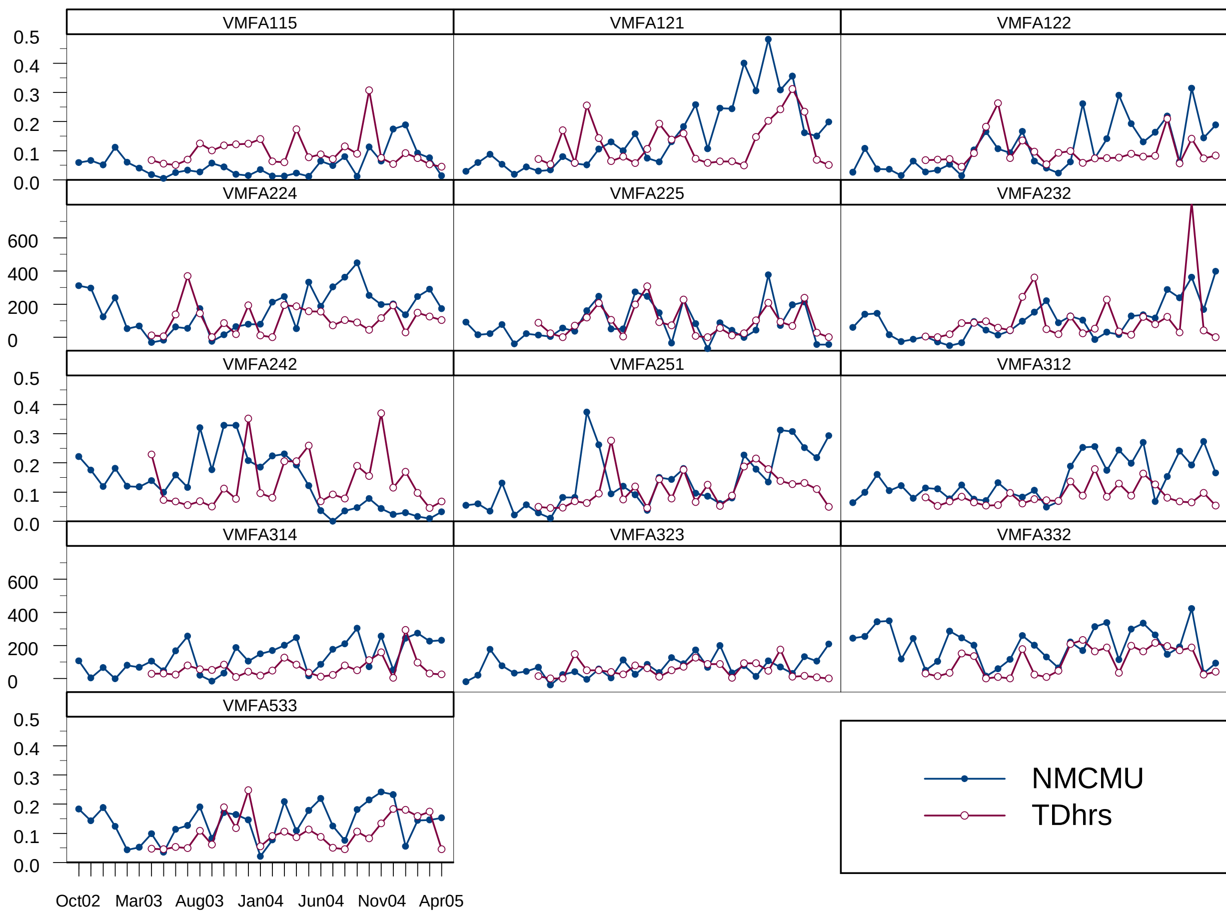

Figure 7 NMCMU and TD Hours by Month by Squadron Time Series

For some squadrons, such as VMFA225 and VMFA332, there appears to be related movement between the *TD hours* and *NMCMU* metrics. To a certain extent, therefore, we may be describing the same performance issue with two different metrics. Without considering the number and type of the TDs scheduled, *TD hours* reflect the type/model/series aircraft requiring them more so than the performance of the maintainers. Since the squadrons are not usually under immediate pressure to complete TDs, the month in which they are scheduled, started, and completed is not captured in sufficient detail to develop a better metric. A more detailed analysis is required to quantify the portion of maintenance that is directly attributable to the incorporation of TDs, normalized by the total number of TDs scheduled for action.

2. Descriptive Metrics

With performance measures identified, we next identify a set of predictor variables to statistically explain these measures. From this point forward, we limit our focus to *man-hours per maintenance action* as our dependant variable, to demonstrate the viability of our analytical approach. We examine the predictor variables within broad categories of operational, personnel, inventory, and technical support metrics.

We can quickly check for correlation between the response variable *man-hours per maintenance action* and our predictor variables with pairwise scatterplots, which are shown in Appendix D. The plots do not indicate any obvious correlation between the response variable and the predictors. This plot also provides an opportunity to eliminate redundant predictor variables. None of the scatterplots cause us to eliminate variables at this point.

a. Operational Metrics

Deployment status. As described in Chapter II, *deployment status* categorizes the overall operational context of a squadron at a moment in time into one of four levels: “IRAQ,” “UDP,” “CVN,” and “CONUS.” “IRAQ” identifies those high-priority deployments such as those in support of Operation Enduring Freedom and Operation Iraqi Freedom. These particular operations were supported by both land-based and carrier-based aircraft during February – May 2003, and again in the months following September 2004. As indicated in

Figure 8 , the land-based squadrons that participated in the 2003 operations—VMFA-121, VMFA-225, VMFA-225, and VMFA-533—flew nearly three times their normal monthly flight hours, and carrier-based squadrons exhibit spikes in flight hours as well.

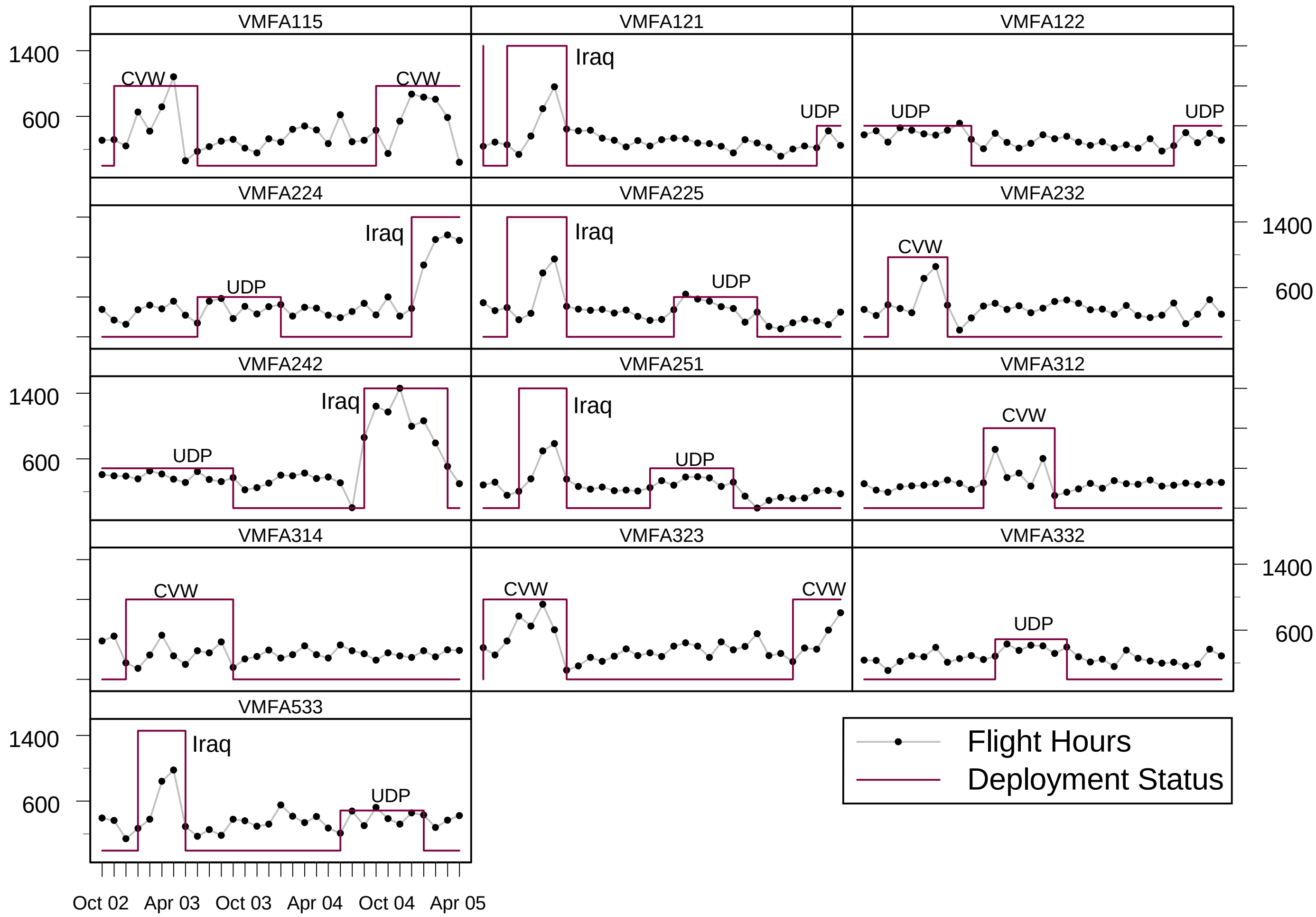

Figure 8 Flight Hours per Month and Deployment Status for Marine Corps F/A-18 Squadrons.

Each panel represents a separate squadron's set of observations for the 31 months between October 2002 and April 2005. The *deployment status* categorical variable has four levels:

"Iraq," which indicates a combat deployment in support of Operation Iraqi Freedom
"CVW," which indicates a deployment with a carrier air wing
"UDP," which indicates a deployment with the Unit Deployment Program
"CONUS," which indicates that the squadron is operating within the U.S.
Unlabeled portions of the *deployment status* plot are of the CONUS level.

Other levels of this metric include “CVN” and “UDP,” which indicate the unit’s participation in a carrier deployment or Unit Deployment Program deployment (UDP), respectively. The UDP program rotates squadrons to bases in the Western Pacific Theater of Operations for six-month deployments at regularly scheduled intervals. Since the deployment metric moves in discrete jumps every few months, it can not explain month-to-month variations in performance. However, it may allow us to explain some of the variance in performance by representing those characteristics that are not explicitly included – morale, urgency, and prioritization.

b. Personnel Metrics

Intuitively, the performance of a squadron is related to the quality of personnel conducting its work. Our challenge is to identify metrics that capture attributes of personnel quality. If we consider the workforce as a dynamic entity that accumulates knowledge and experience over time, then the quality of a squadron workforce might be expressed as a sum of these factors. Likewise, with the loss of experienced personnel comes a loss in the aggregate experience of the squadron. We use three metrics to capture this phenomenon: *months of service*, *months in squadron*, and *turnover*.

Months of Service. Again, we expect to see a relationship between the capability of the workforce and the quality of work it produces. Capability, while not directly measurable, may be reflected in the experience of the squadron maintainers. We first define experience as *months of service*, which indicates the total number of months the maintainer has been on active duty. From personnel data, the individuals’ *months of service* is noted at the end of each month. Figure 9 shows histograms of months of service for the maintainers of the squadrons in our study. It is clear that the distribution of experience is not symmetrical.

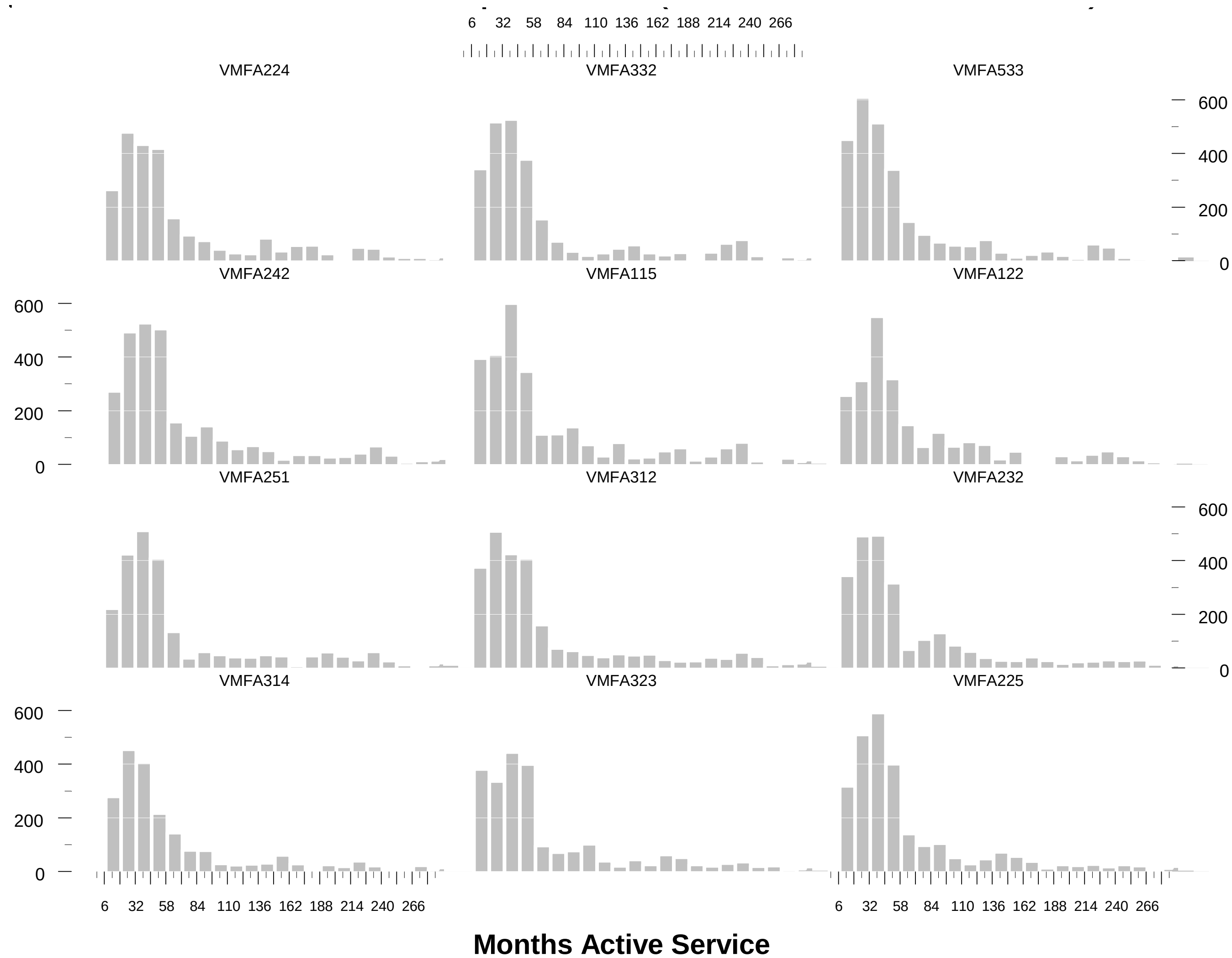

Figure 9 Distribution of Months of Experience of Squadron Maintainers. Each panel represents twenty months of data, from May 2003 to December 2004, for each of the squadrons in our study. Data represents maintenance personnel only, and was not obtained for VMFA-121. Squadron labels are located above each histogram. Horizontal axis labels represent months active service; vertical axes represent numbers of personnel.

The fact that all squadrons exhibit a skewed distribution of *months of service* suggests that most individuals' experience levels lie below the squadron mean, which ranges from 62.4 months of service (VMFA533) to 73.3 months of service (VMFA251). Some squadrons do appear to have a wider spread of experience levels than others, which may be even more pronounced when viewed across time. We use the first quartile, second quartile (median), and third quartile together to capture these shape characteristics. For a given month, the value of the first quartile indicates that 25 percent of the maintainers in the squadron have that many or fewer months on active duty. These quartiles are plotted as a time series in Figure 10 . The plots suggest that the second quartile may contain redundant information, so we will include only the first and third quartiles when considering them for model inclusion.

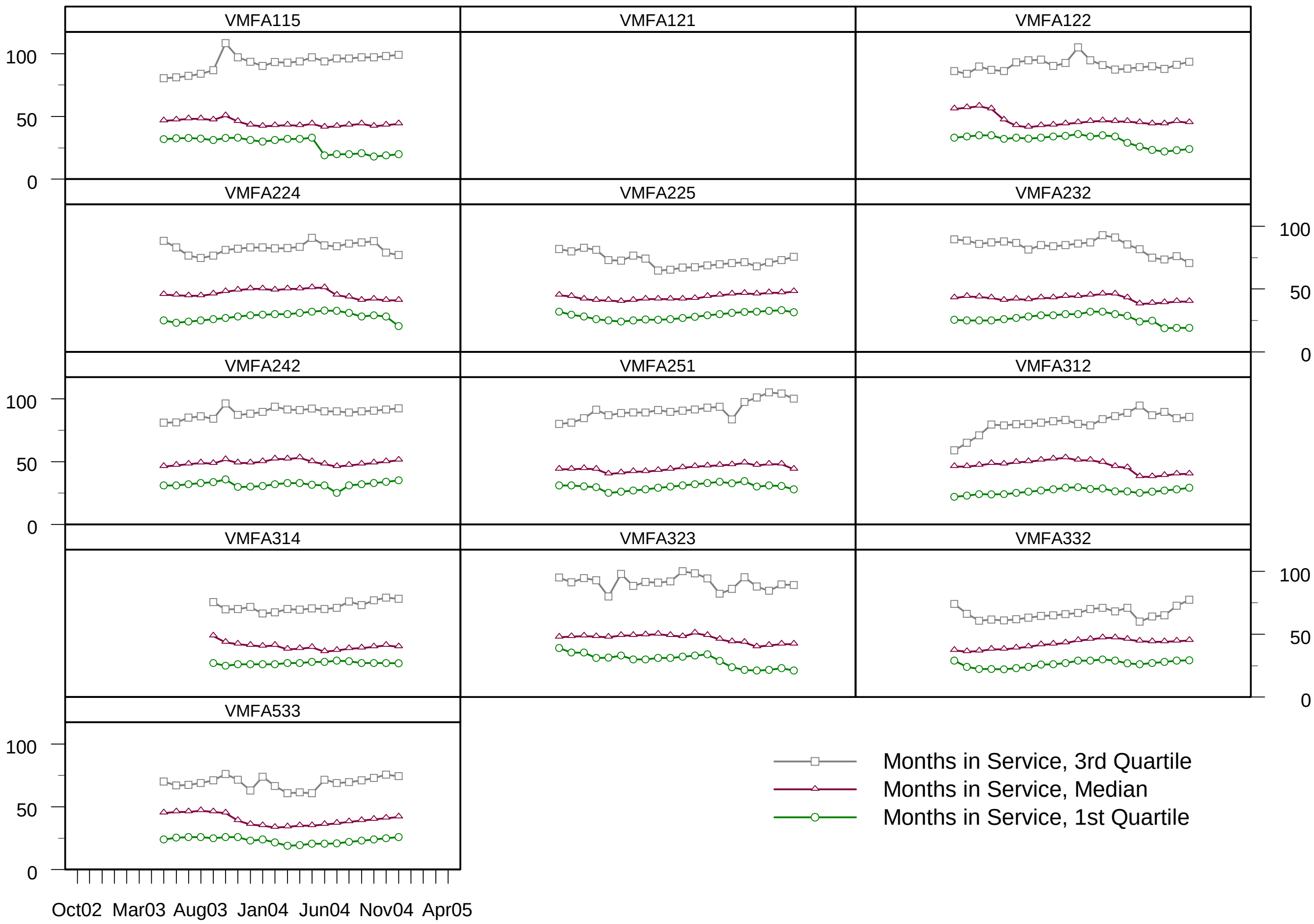

Figure 10 Months of Service Quartiles Time Series.
Each panel represents 20 months of the *months of service* quartiles from May 2003 to December 2005 for active duty Marine Corps F/A-18 squadrons. Data for VMFA-121 was not obtained.

As Figure 10 shows, the time series exhibit significant movement during the period of our study. VMFA251 appears to exhibit an increasing experience level in the upper quartile, whereas VMFA232 and 225 show declines. Furthermore, the movement of the experience level of the lower quartile does not necessarily correspond to that of the upper quartile, as seen with VMFA115 and VMFA122.

Months in Squadron. If the average accrued time spent in a squadron is relatively low, we would expect performance to suffer to some degree. Figure 11 depicts the movement of the *months in squadron* quartiles over time for each of the squadrons.

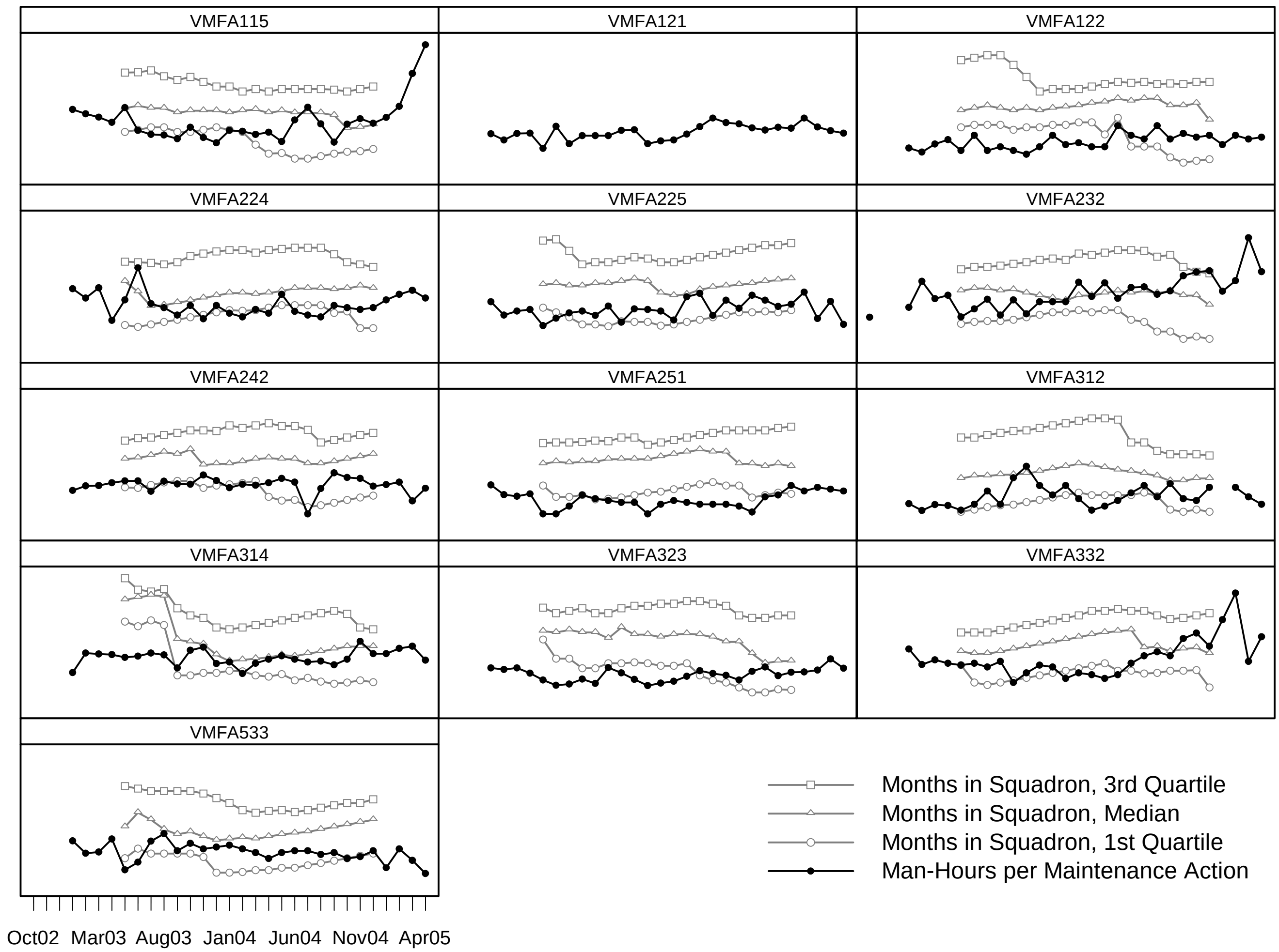

Figure 11 Maintainer Months in Squadron Quartiles Compared to Man-Hours per Maintenance Action (MMHperMA)

During the two-year period under investigation, we see significant drops in squadron experience for some squadrons, and increases for others; again, the upper and lower quartiles do not necessarily correspond. When viewed in relation to the man-hours performance metric, we don't see obvious correlation, so it is difficult to prefer one particular quartile over another at this stage.

Turnover. In addition to varying experience levels of the personnel in the squadron, we know that squadrons experience a certain amount of turnover—a function of people entering and leaving the organization in any given month. Figure 12 depicts the turnover quantities by month, by squadron.

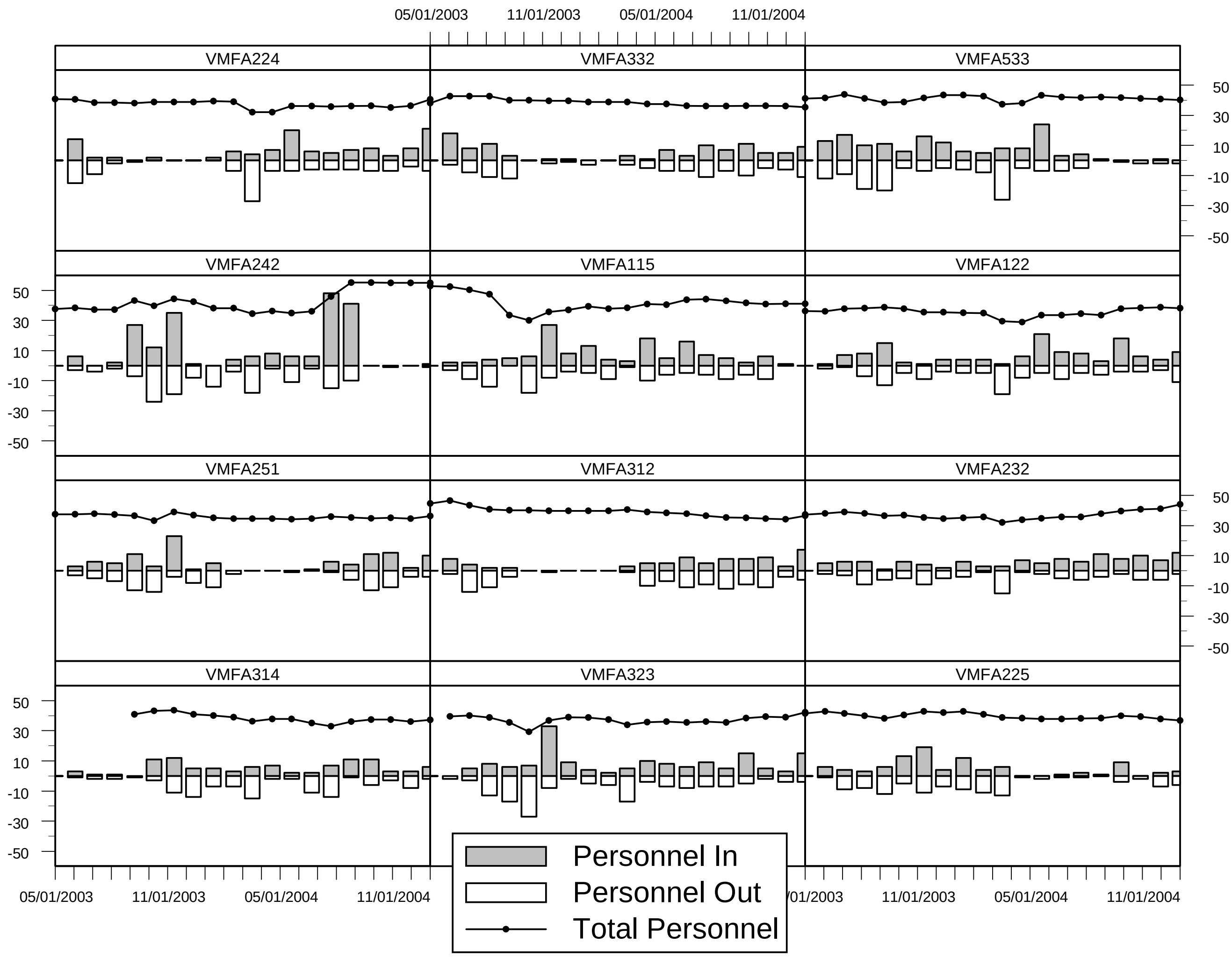

Figure 12 Maintenance Personnel Movement for Marine Corps F/A-18 Squadrons.
The panels represent personnel data for the 20 months between May 2003 and December 2004. Data for VMFA-121 was not obtained. The grey bars above the horizontal line show the number of maintainers that entered the squadron during the corresponding month, on a scale from 0 to 60. Similarly, the bars below the horizon line indicate the number of maintainers that departed, on a scale from 0 to -60. The total number of maintainers in the squadron is shown as well, on a scale from 0 to 200.

We can see significant quantities of inbound and outbound personnel at specific times during the period under investigation. We capture the turnover information in a single metric in which we calculate the total number of inbound and outbound maintenance personnel as a percentage of the total. We might expect units with especially high turnover rates to struggle with maintenance performance. Figure 13 depicts the turnover for each squadron as a time series.

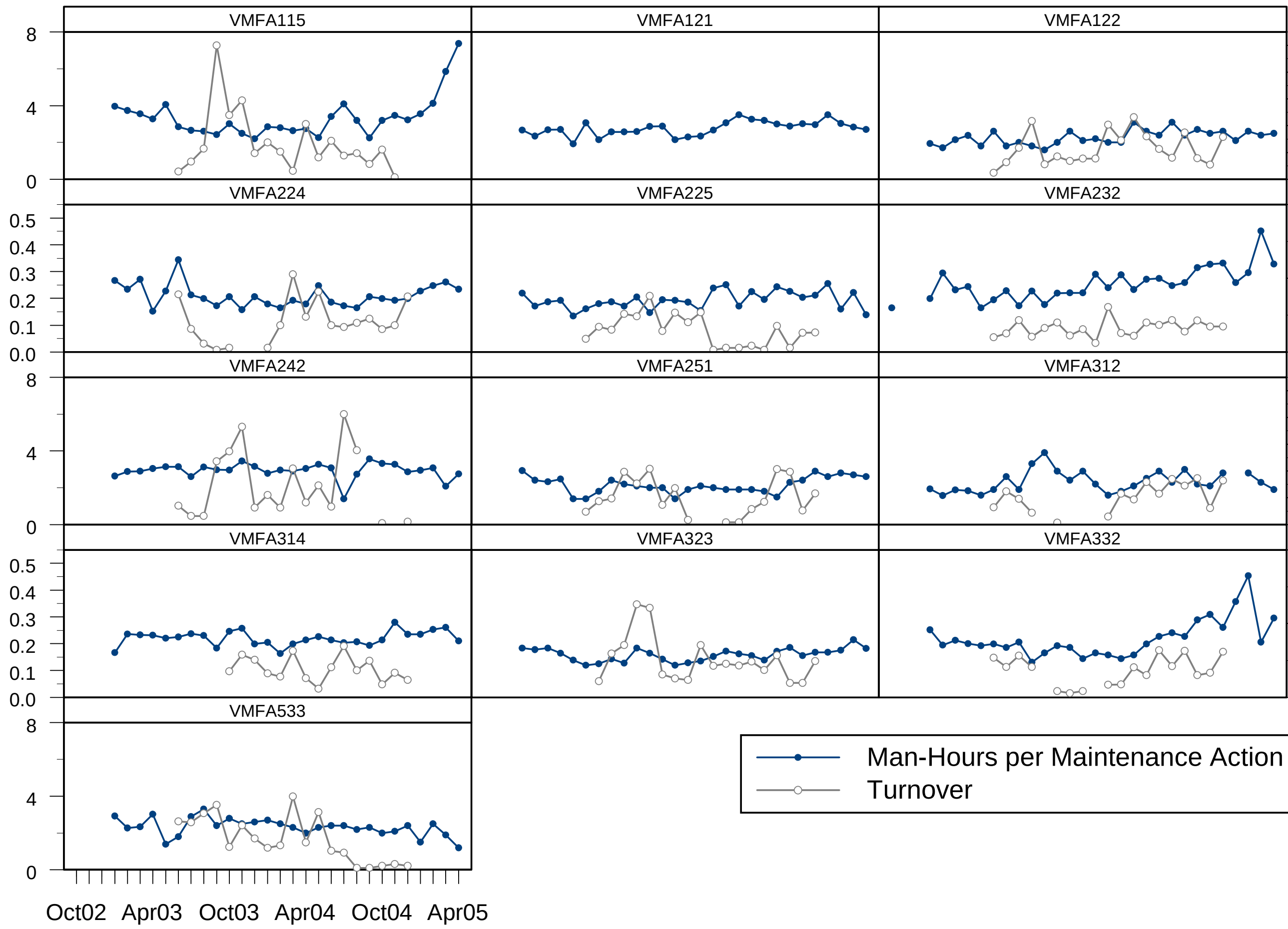

Figure 13 Maintenance Personnel Turnover by Squadron Time Series Compared to Man-hours per Maintenance Action (MMHperMA).
Each panel represents observations from an individual Marine Corps F/A-18 squadron. Squadron labels are above each plot. *Turnover* is defined as the total number of maintenance personnel into and out of the squadron as a proportion of the total number of maintenance personnel. The vertical axis for *turnover* ranges from 0 to 0.5.

It is apparent that the squadrons occasionally experience relatively high levels of turnover, such as VMFA314 and VMFA323. We might expect the squadrons to benefit from a stable manpower base and likewise to suffer from an environment of high personnel turnover. With respect to our performance metric, *man-hours per maintenance action*, the time series plot shows little direct correlation to *turnover*.

c. Inventory Metrics

We might reasonably expect older aircraft to exhibit higher failure rates and require additional maintenance when compared to newer aircraft. The inventory of F/A-18 aircraft operated by the squadrons under investigation differ significantly in their age in terms of months of service and accrued hours flown. Figure 14 depicts time series of box plots that show the distribution of accrued hours on the squadrons' inventory of aircraft. The oldest lots of aircraft included in this data came off the production line in 1986; the newer aircraft, by contrast, were accepted by the operating forces in 2000. We can see that the older aircraft have nearly twice the accrued flight hours as that of those that operate newer lots of aircraft. When viewed as a time series, we see the average ages of aircraft in each squadron slowly increase as we might expect. We also see sudden rises and falls of the averages, attributable to those points in time where squadron exchanged aircraft for operational and service life extension reasons. These particular points of aircraft exchange may themselves be an explanatory factor to a performance measure.

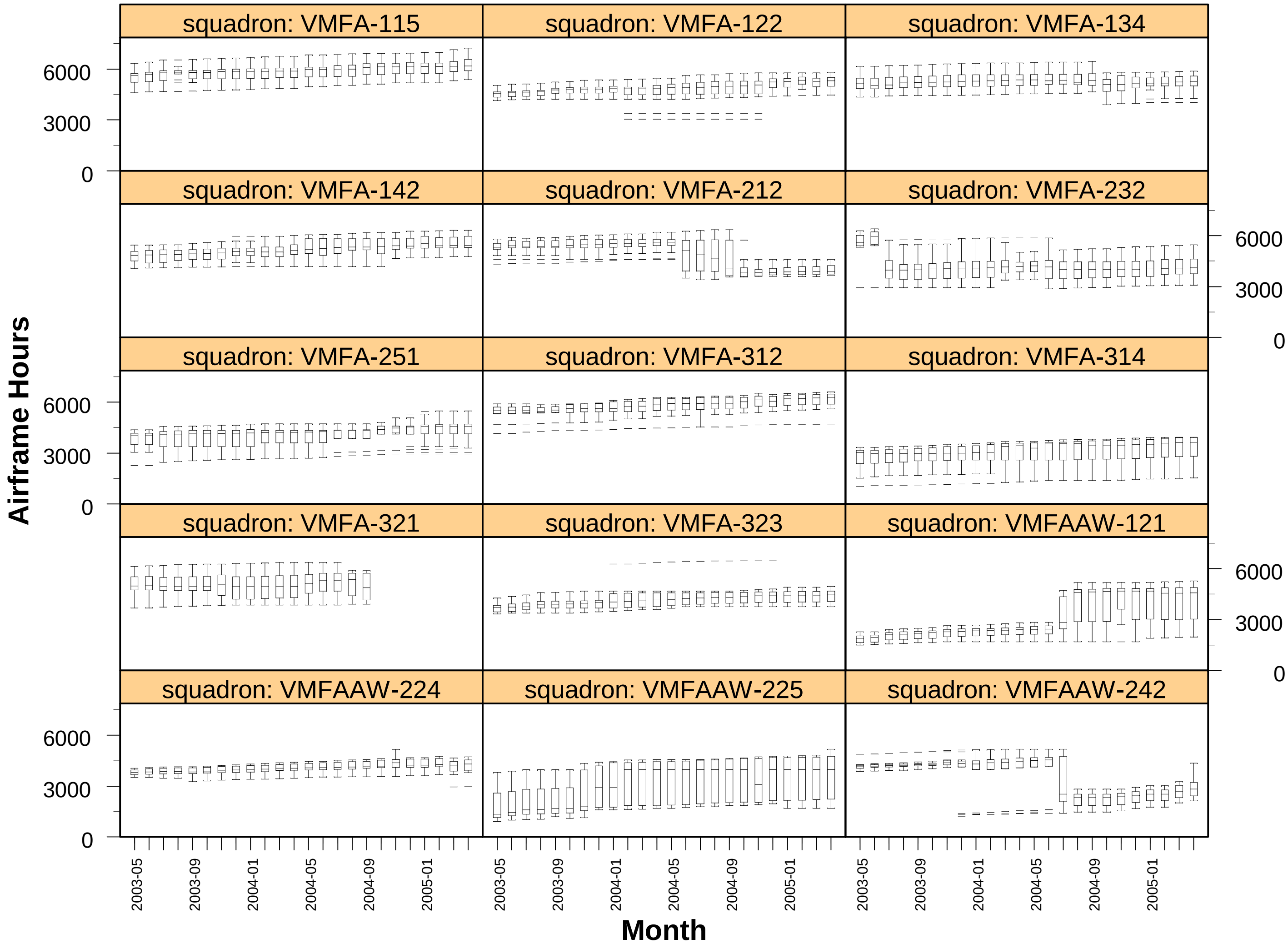

Figure 14 Boxplots of Airframe Hours by Squadron.
Each panel represents a time series of boxplots for the 24 months between May 2003 and April 2005. Each squadron is normally assigned twelve aircraft; therefore, each boxplot represents the age distribution (in hours flown) of the squadron's inventory of aircraft, for the corresponding month. The box represents all data between the 25th and 75th percentiles. The line inside the box represents the median of the distribution. The vertical lines that extend above and below the box represent the range of data; horizontal tick marks outside these ranges represent outliers.

We reduce the aircraft age distributions to a single metric, *average aircraft hours in service,* and plot the time series of this average along with *man-hours per maintenance action* in Figure 15 . The plot does not suggest an obvious relationship between the aircraft age and our performance metric *man-hours per maintenance action*.

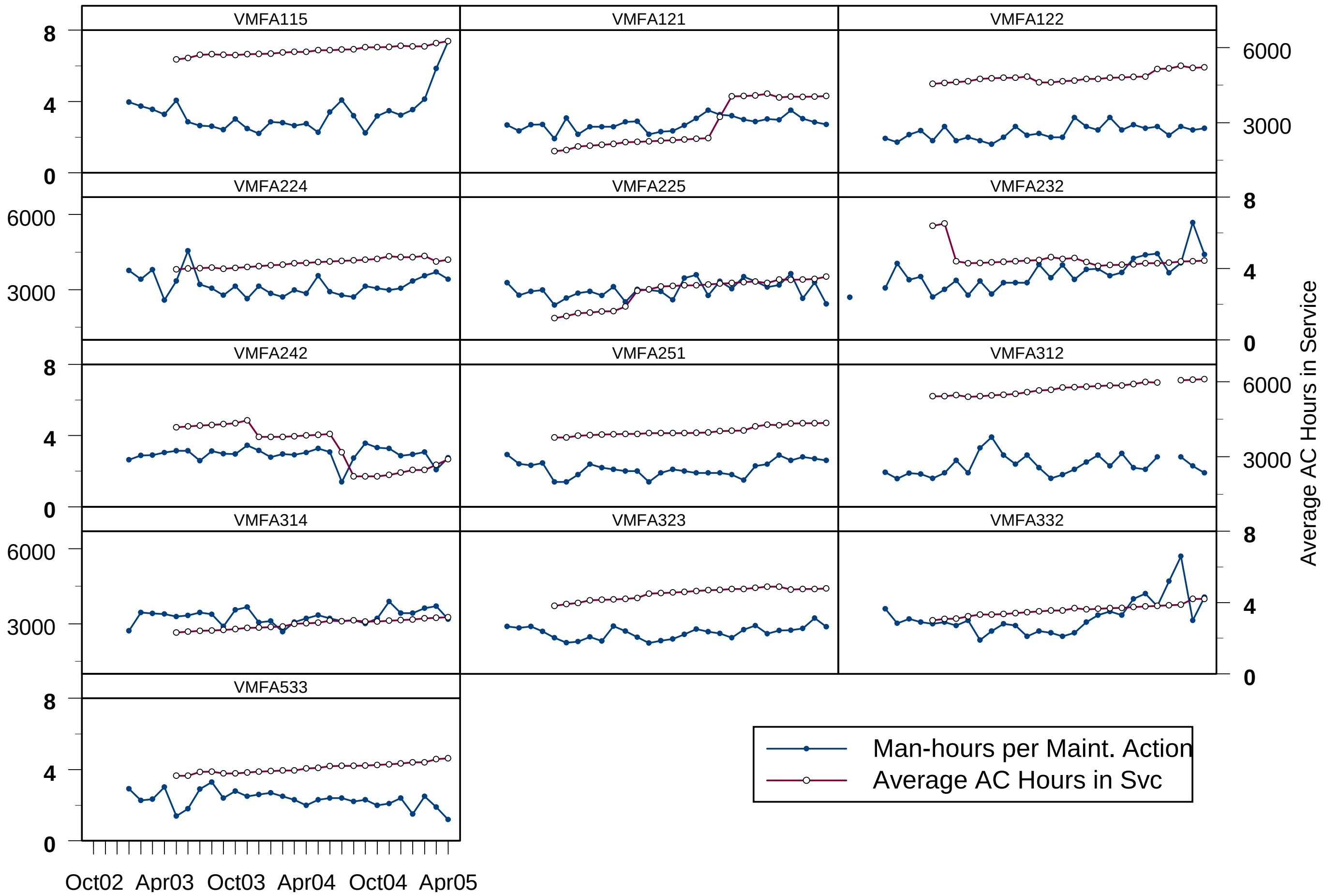

Figure 15 Mean Aircraft Hours in Service Compared to Man-Hours per Maintenance Action (MMHperMA).
Each panel represents 28 months of the *man-hours per maintenance action* metric, for the months between January 2003 and April 2005, for Marine Corps F/A-18 squadrons. MMHperMA is shown on a scale ranging from 0 to 8. Average *aircraft hours in service* metric is shown on a scale ranging from 1500 to 6000 hours.

d. Engineering and Technical Support (ETS) Metrics

The entry screen for new ELAR records is shown in Appendix B. Our goal is to identify metrics related to tech rep utilization that may exhibit relationship with performance measures at the squadron level. We simplify the search by eliminating ELAR data fields that pertain to subjective comments, descriptive text, and freeform feedback.

Each time a customer initiates a request for ETS support, a new ELAR record is generated. Theoretically, the demand for ETS support, reflected by the number of tech rep requests received, corresponds with the number of records in the database. During the period August 2003 to April 2005, ELAR contains 6,249 records for which the program is categorized as “F-18.” Not all squadrons use ELAR with the same regularity, as shown in Figure 16 . We are interested in records that can be attributed to a particular squadron. However, of these 6,249 F/A-18 records, only 3,176 of these (51 percent) attribute the tech rep action to a specific squadron. The situation is improving: after January 2005, the squadron data field is almost always present. This improvement notwithstanding, we are left with a very short time frame in which to study the effects of tech rep actions on squadron performance, using reliable data.

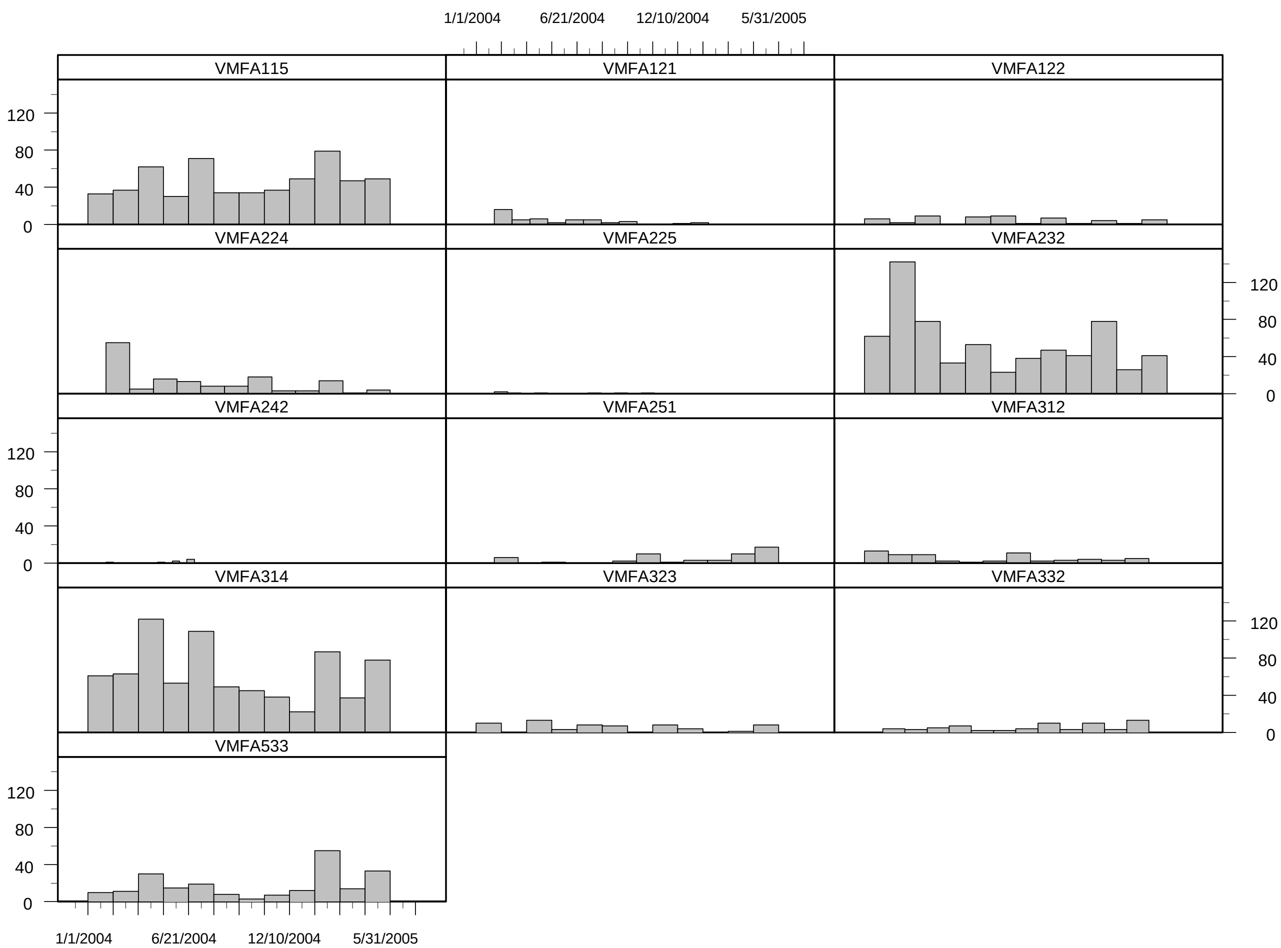

Figure 16 Distribution of Monthly ELAR Records.
Panels show the time-series distribution of ELAR records between January 2004 and June 2005.

The distribution shows a sharp decline in the number of records during July and August 2004. Either ETS support decreased during this time period or the tech reps' documentation in ELAR diminished for some other reason unknown to us.

We expect the volume of ETS requests to vary by type of support offered. An important role of the tech reps is to provide specific training that augments the basic skills training of the maintainers obtained after they complete recruit training and prior to their arrival at their first unit. Such skill training is usually unique to a specific work center and is conducted during formal and informal training in short periods as the schedule permits. Since the conduct of this training is not standardized in its conduct or in its documentation, we do not quantify it directly in this study. However, the tech reps themselves conduct a portion of this training and document such activities as formal training and on the job training in their ELAR database.

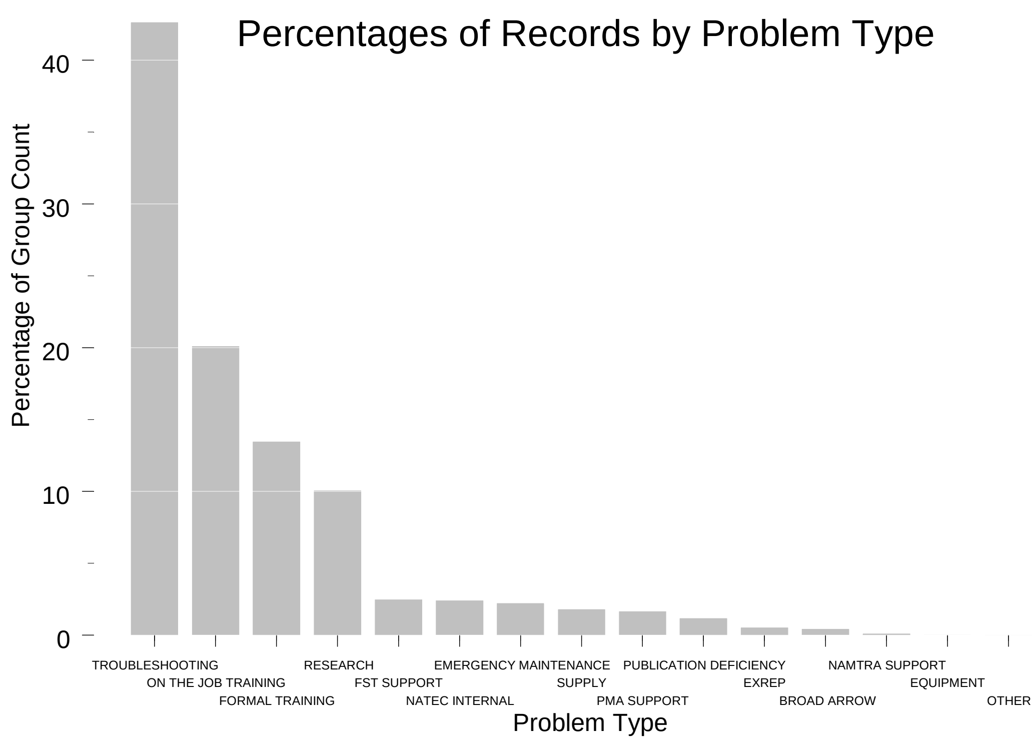

Figure 17 Pareto Chart Distribution of F/A-18 ELAR Records by Problem Type
The chart includes the 6249 ELAR records recorded between August 2003 and April 2005. The most common problem types—troubleshooting, on-the-job-training, formal training, and research—account for nearly 90 percent of all records. The vertical axis is a percentage scale.

In addition to records that are associated with training squadron personnel, we can identify any other ETS metrics that are most often documented by the tech reps and the requesting units. Figure 17 depicts a Pareto plot of the distribution of records by problem type. The first four categories of problem type—troubleshooting, on-the-job-training (OJT), formal training, and research—account for nearly 90 percent of F/A-18 ELAR records; we therefore limit consideration to these problem types. We sum the monthly records into a single ELAR metric and plot the changing values as a time series, as shown in Figure 18 , compared to the performance metric *man-hours per maintenance action*.

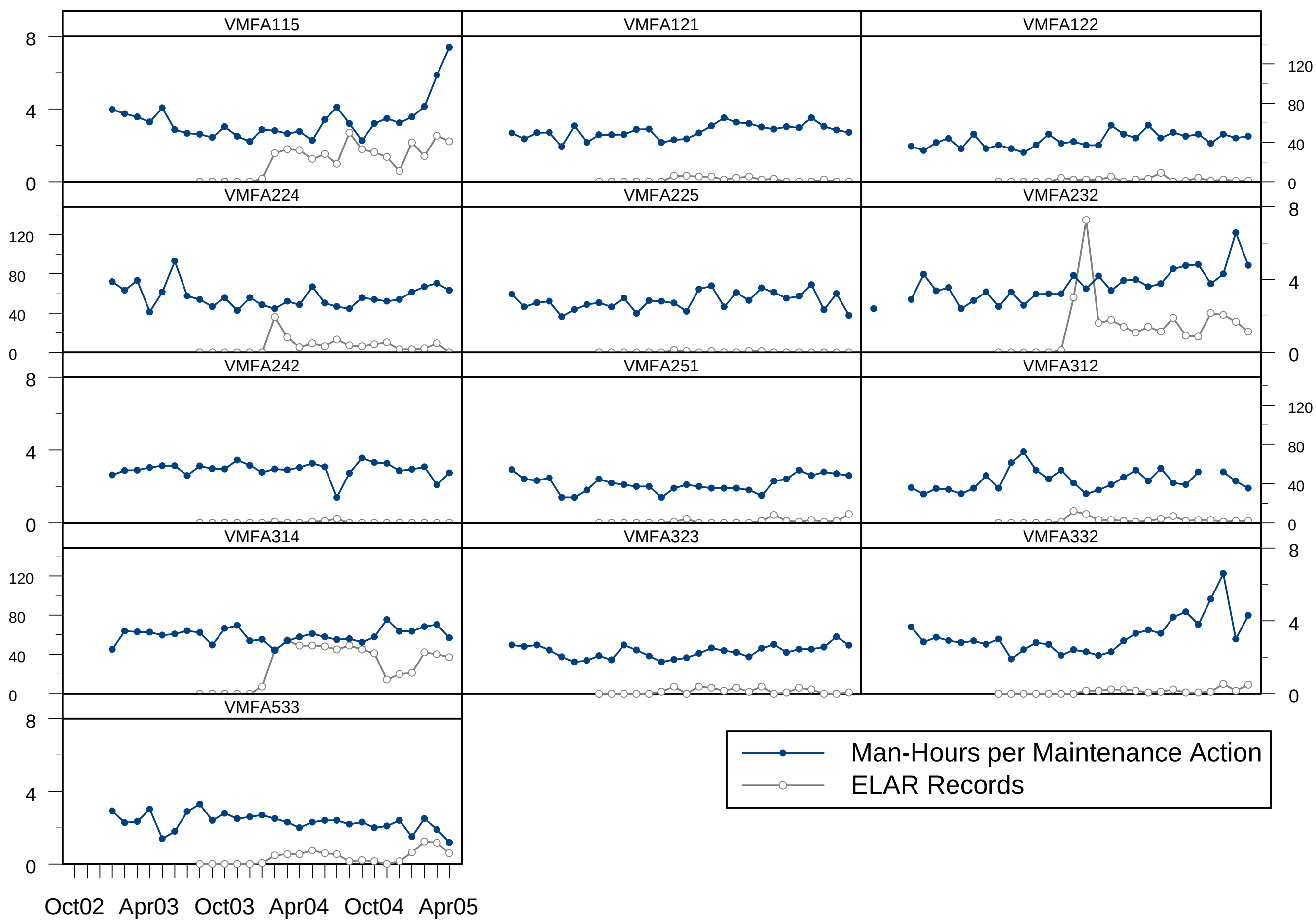

Figure 18 ELAR Records Compared to Man-Hours per Maintenance Action. Each panel represents data for a Marine Corps F/A-18 squadron. ELAR records are limited to the 21 months between August 2003 and April 2005 and to records that can be attributed to a specific squadron.

Figure 18 indicates that some squadrons, such as VMFA-115, VMFA-232, and VMFA-314, report much higher numbers of records on average; it is possible that these squadrons have different policies or procedures regarding their compliance with ELAR. To build an accurate explanatory model that includes ELAR record counts, we would need to explore records with the squadron field missing in detail, which is beyond the scope of this research. Chapter III.E. outlines the approach we take when analyzing the power of ELAR activity in predicting performance variability. Chapter IV discusses improvements in the ELAR database tool that could improve analysts' ability to measure tech rep activity accurately.

e. Location

Each squadron is associated with a particular location, or home station, as listed in Table 1. We are interested in knowing whether some of the variability of *man-hours per maintenance action* can be explained by the location of the squadron. We create a two-level categorical variable *location* to capture this factor. Figure 19 shows the distribution of *man-hours per maintenance action* for the two levels of *location*.

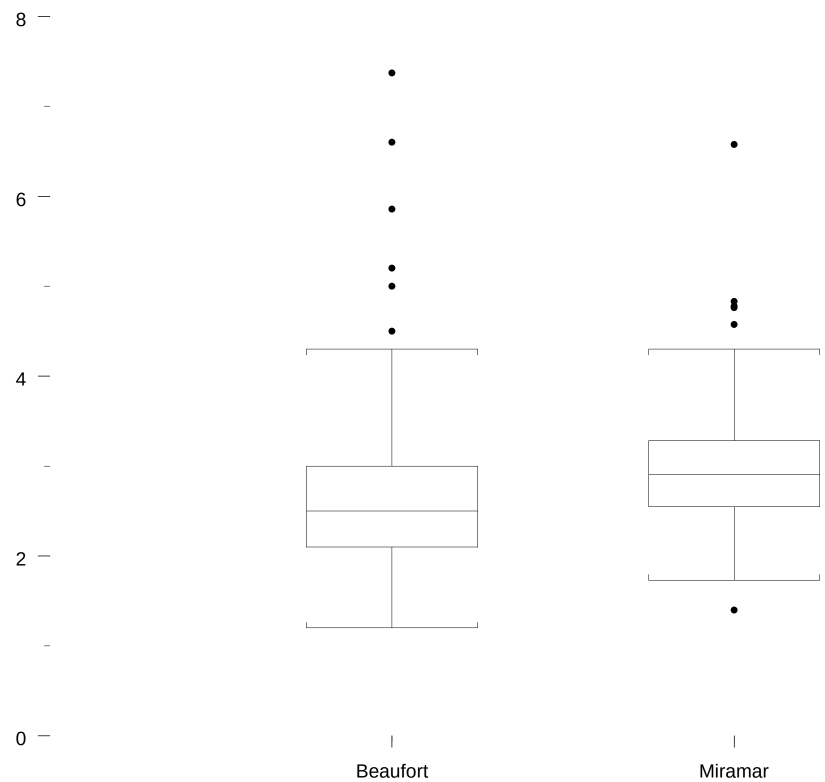

Figure 19 Boxplots of Man-Hours per Maintenance Action by Location. Each boxplot shows the distribution of *man-hours per flight hour* for the 31 months of data between October 2002 and April 2005. The two boxplots are for Marine Corps F/A-18 squadrons based at MCAS Beaufort and MCAS Miramar, respectively. The box represents all data between the 25th and 75th percentiles. The line inside the box represents the median of the distribution. The vertical lines that extend above and below the box represent the range of data; dots outside these ranges represent outliers.

Figure 19 indicates that there is a small difference between the distributions of Beaufort and Miramar observations with respect to *man-hours per maintenance action.*

f. Operational Metrics

As discussed in Section C.2. of this chapter, the Marine Corps executes a cyclical readiness policy whereby units that are nearing deployment enjoy a focus of effort and maintain a high state of readiness. Conversely, returning units receive lower priority and may expect to achieve a lower state of readiness. Factors such as personnel morale and sense of urgency are also affected by the operational status of the squadron. Since we are aware of these phenomena, we consider *deployment status* as an explanatory factor in the variability of *man-hours per maintenance action*. Figure 20 shows a time series plot of both the performance measure *man-hours per maintenance action* and *deployment status*. The plots alone do not suggest a direct relationship between the two metrics.

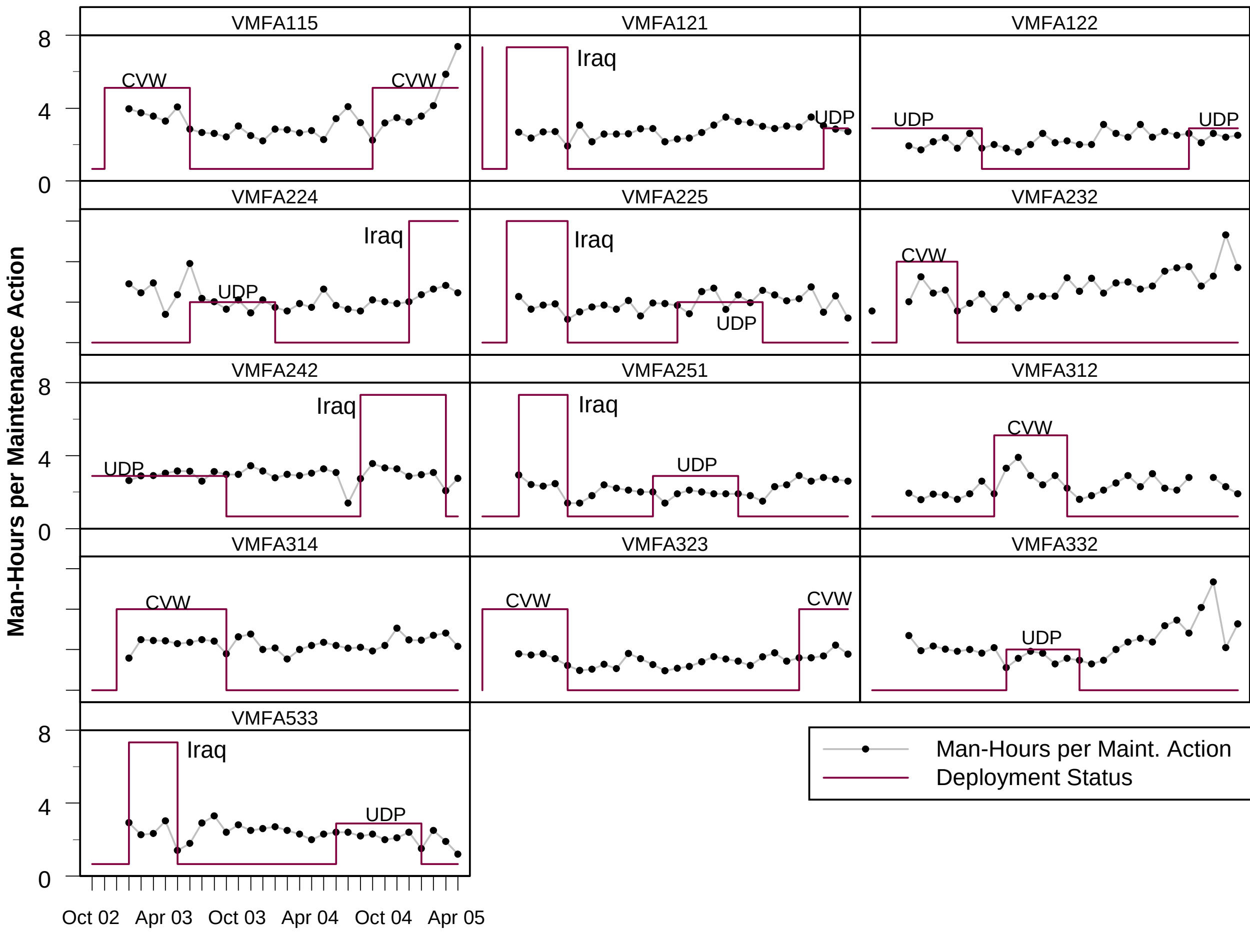

Figure 20 Deployment Status Compared to Man-Hours per Maintenance Action and Deployment Status.

The man-hours performance metric does not appear to be affected by deployment status. We might expect operational deployments to result in an increased performance level, reflected in fewer man-hours per maintenance action; however, we can not draw this conclusion from the plots alone.

g. *Summary of Exploratory Analysis*

We have compiled several variables that we believe may be significant in explaining variability of squadron maintenance performance. These variables are listed in Table 3.

Variables	Source	Data Fields Used	Data Range
Man Hours per Maint. Action	NALCOMIS	man-hours, maintenance actions	Oct 02 – Apr 05
Months of Service Quartiles	MCTFS	months active service, months active service	May 03 – Dec 04 May 03 – Dec 04
Months in Squadron Quartiles	MCTFS	date of record, date arrived duty station	May 03 – Dec 04
Turnover	MCTFS	arrived date, record date	May 03 – Dec 04
Average Aircraft Hours in Service	NAVAIR	hours in service	May 03 – Apr 05
ELAR Records	ELAR	N/A	Aug 03 – Apr 05
Deployment	Various	N/A	Oct 02 – Apr 05
Flight Hours	NALCOMIS	flight hours	Oct 02 – Apr 05
Location	N/A	N/A	Oct 02 – Apr 05
Type Equipment Code	NALCOMIS	type equipment code (TEC)	Oct 02 – Apr 05
Organization	N/A	N/A	Oct 02 – Apr 05

Table 3. Table of Potential Predictor and Response Variables.
Data used in the calculation of the variables in the table are calculated on a monthly basis. For personnel data, *months in squadron* is determined by subtracting the month the individual arrived at the duty station from the current month of record. *Turnover* is calculated by summing inbound and outbound personnel and dividing by the total number of maintenance personnel in the squadron. Inbound personnel are counted by summing those records, in the given month, for which arrived date equals the date of the record.

In the next section we explain the model selection and estimation process, using the performance measure *man hours per maintenance action* as the response variable and the other variables of Table 3 as predictor variables.

D. PREDICTOR VARIABLE CORRELATION

Before beginning model selection process, we examine the set of predictor variables for indications of redundancy. Figure 21 shows a scatterplot of variables pertaining to personnel experience.

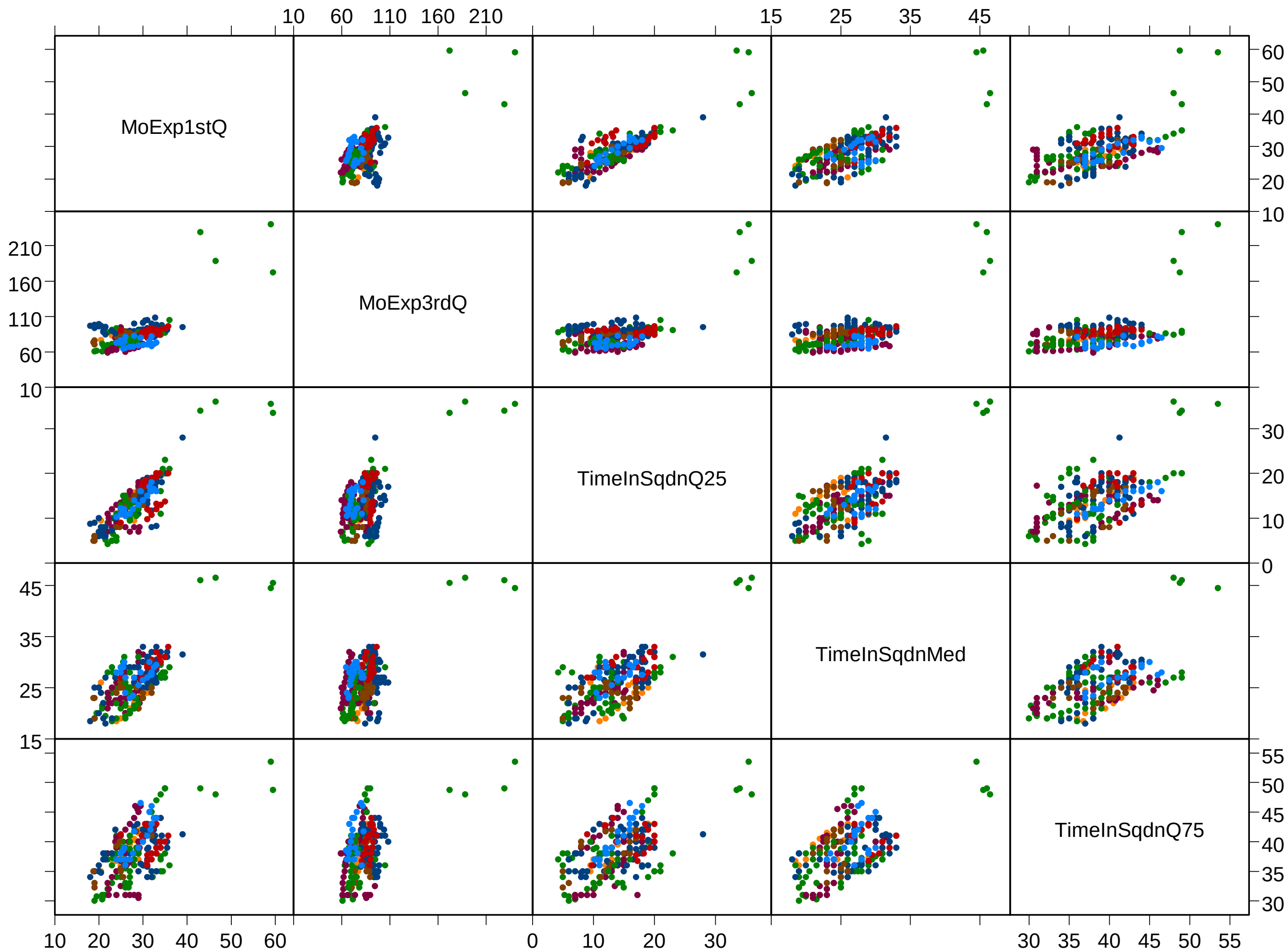

Figure 21 Personnel Experience Metric Pairwise Scatterplots.
Each panel represents 240 observations: 20 months of data between August 2003 and December 2004 for 12 active duty Marine Corps F/A-18 squadrons. Personnel data from VMFA-121 is not included.

The pair-wise scatter plots suggest fairly high levels of correlation between these metrics. The correlation value between *months in squadron*, first quartile (TimeInSqdnQ25) and *months in service*, first quartile (MoExp1stQ), is 0.81. The use of highly correlated predictor variables increases estimation error, and makes it difficult to attribute effects to particular variables. Pair-wise scatter plots of the remaining metrics, not including the categorical variables *TEC*, *deployment*, *location* or *organization*, can be found in Appendix D.

E. MODEL BUILDING

With potential areas of multi-collinearity identified, we turn to the problem of determining the best combination of the predictors that explain our chosen response variable, *man-hours per maintenance action*. For the analysis, we use an ordinary least squares (OLS) linear regression to develop an explanatory model. The data set we use contains 403 observations of 11 predictor variables. However, since some observations contain missing values, the actual number of observations used in model estimation depends on which variables are included. When including all eleven predictors, we have 20 months of complete data for 12 of the 13 Marine Corps F/A-18 squadrons. Several months of the personnel variables are thought to be erroneous and are omitted, leaving a total of 209 observations with no missing values.

Each of the k levels of the categorical variables—TEC, location, deployment, and organization—are automatically assigned $k-1$ "dummy" variables by the statistics software. For our analysis, we use S-Plus® version 6.2 [Insightful Corporation, 2003]. Table 4. lists the variable abbreviations shown in S-Plus reports:

S-Plus Abbreviation	Variable
TECAMAA TECAMAF TECAMAG	Type equipment code = "AMAA" (F/A-18A) Type equipment code = "AMAF" (F/A-18C) Type equipment code = "AMAG" (F/A-18D)
AvgAircraftHrsInSvc	Average aircraft hours in service
MoExp1stQ/2ndQ/MoExp3rdQ	Months in service, first quartile/second quartile/third quartile
TimeInSqdnQ25/Med/Q75	Months in squadron, first quartile/second quartile/third quartile
Flthrs	Flight hours
Loc	Location = "Miramar"

Table 4. Variable Coding and Abbreviations in S-Plus Reports.

We know that the squadrons' performance levels differ during any given month, but our goal is to identify those characteristics that differentiate the squadrons in this respect. We therefore begin by building a least-squares regression model without the *organization* term to see how much of the variability can be explained by underlying squadron characteristics. Montgomery, Peck, and Vining [2001] give a thorough explanation of linear modeling using least squares regression. Finally, we address the first three study questions posed in Chapter I:

1. Which squadron characteristics have a detectable contribution to the variability of the performance measure *man-hours per maintenance action*?
2. How much additional variability is explained by the squadron that is not accounted for by the squadron characteristics already considered?
3. Is there a time-of-year effect for the performance of the squadrons?

We begin by identifying a statistical model that will apply to all squadrons similarly, using measurable characteristics of the squadrons. We then compare this model to one that includes the *organization* term, which captures the squadrons directly. Although the latter model may have better explanatory power than the former model, it lends less insight into why a particular squadron may perform differently from another. By using squadron characteristics to capture this effect, we explain maintenance performance in a manner that is applicable beyond the thirteen squadrons that were included in our research.

1. Full Models

We begin our modeling effort by identifying the linear combination of predictor variables that best explains or predicts *man hours per maintenance action*. Using the linear regression utility in S-Plus, the initial full model includes all potential predictors as main effects variables. However, rather than include *organization* in the model, we proceed with the regression without an *organization* term and then analyze the distribution of residuals by organization. This process will allow us to analyze the added explanatory power of the added *organization* term.

We express the response variable as a linear combination of predictor variables plus an error term. Formally,

$$\begin{aligned} Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \\ \beta_6 X_{6,s,t} + \beta_7 X_{7,s,t} + \beta_8 X_{8,s,t} + \beta_9 X_{9,s,t} + \beta_{10} X_{10,s,t} + \beta_{11} X_{11,s,t} + \varepsilon_{s,t} \end{aligned} \tag{1}$$

where

$Y_{s,t}$ = man-hours per maintenance action, squadron s, month t
$X_{1,s,t}$ = type equipment code
$X_{2,s,t}$ = first quartile, months experience
$X_{3,s,t}$ = third quartile, months experience
$X_{4,s,t}$ = average aircraft hours in service
$X_{5,s,t}$ = turnover
$X_{6,s,t}$ = location
$X_{7,s,t}$ = first quartile, months in squadron
$X_{8,s,t}$ = second quartile, months in squadron
$X_{9,s,t}$ = third quartile, months in squadron
$X_{10,s,t}$ = deployment
$X_{11,s,t}$ = flight hours
$\varepsilon_{s,t}$ = residual
k = number of variables
s = squadron
t = month

We have included the full set of predictors in Equation (1). For this model, we have 209 observations with no missing values of these variables. The eleven predictors and the additional levels needed for the categorical variables constitute 14 regression variables plus an intercept term. The plot of the residuals against the fitted values indicates non-constant variance of the residuals. The plot of the residuals against the fitted values suggests that variance of the residuals is not independent of the predicted values. The normal plot of residuals also shows some skewing. We therefore transform the response variable with a natural logarithm transformation. After transforming the response variable accordingly we are left with a full model expressed formally:

$$\begin{aligned} \ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \\ \beta_6 X_{6,s,t} + \beta_7 X_{7,s,t} + \beta_8 X_{8,s,t} + \beta_9 X_{9,s,t} + \beta_{10} X_{10,s,t} + \beta_{11} X_{11,s,t} + \varepsilon_{s,t} \end{aligned} \tag{2}$$

The output from this full regression model in S-Plus is shown in Appendix E. The summary data from this regression is reproduced in Figure 22 .

```
Coefficients:
                        Value Std. Error t value Pr(>|t|)
        (Intercept)   1.2280  0.2453      5.0060  0.0000
            TECAMAF   0.0517  0.0708      0.7304  0.4660
            TECAMAG   0.1865  0.0816      2.2861  0.0233
          MoExp1stQ   0.0011  0.0071      0.1620  0.8715
          MoExp3rdQ  -0.0026  0.0022     -1.1800  0.2395
AvgAircraftHrsInSvc   0.0001  0.0000      1.7798  0.0767
           Turnover  -0.2300  0.2191     -1.0497  0.2952
                Loc   0.2214  0.0389      5.6884  0.0000
      TimeInSqdnQ25   0.0005  0.0065      0.0815  0.9351
      TimeInSqdnMed  -0.0179  0.0057     -3.1402  0.0020
      TimeInSqdnQ75  -0.0090  0.0071     -1.2650  0.2074
      DeploymentUDP  -0.1124  0.0512     -2.1929  0.0295
      DeploymentCVN   0.1827  0.1099      1.6634  0.0978
     DeploymentIRAQ   0.0680  0.2092      0.3249  0.7456
            Flthrs    0.0000  0.0001      0.2025  0.8397
          MoExp2ndQ   0.0064  0.0072      0.8896  0.3748

Residual standard error: 0.212 on 194 degrees of freedom
Multiple R-Squared: 0.2791
F-statistic: 5.007 on 15 and 194 degrees of freedom, the p-value is 2.751e-008
194 observations deleted due to missing values
```

Figure 22 Full Model Summary, S-Plus Report.
The model includes all predictors. The available degrees of freedom are based on the number of observations n = 209. p = 15 (14 variables plus the intercept) leaving 194 degrees of freedom. R^2 is derived by dividing error sums of squares by total sums of squares and subtracting from 1. The F-statistic is based on p-1=14 and n-p=225 degrees of freedom. Variables are abbreviated in S-Plus. TEC = *type equipment code*; MoExp1stQ = *months in service*, first quartile; AvgAircraftHrsInSvc = *average aircraft hours in service*; TimeInSqdn = *months in squadron*; Loc = *location*; Flthrs = *flight hours*.

An initial indication of the model's ability to explain the variance is seen in the R^2 value. The R^2 value is calculated by dividing the error sums of squares by the total sums of squares and subtracting from 1. As seen in Figure 22, R^2 for the full model is 0.279. This R^2 suggests that approximately 28 percent of the variability is explained by this model. However, not all individual variables are significant in the presence of the others, as indicated by their p-values. *Months in squadron* (first and third quartiles), *months in squadron* (first and third quartiles), and *turnover* appear to be insignificant, at the 5% level, in the presence of the other variables in this model.

2. Significant Variables and Model Reduction

We proceed with stepwise regression to reduce the model to the smallest model that retains significant terms. This is implemented in S-Plus software through the `stepwise` function, which uses Akaike's Information Criterion (AIC) to determine the best reduced model [Insightful, 2001]. The results of the stepwise process are shown in Appendix F. Equation (3) expresses the reduced model.

$$\begin{aligned}\ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \\ \beta_5 X_{5,s,t} + \varepsilon_{s,t}\end{aligned} \tag{3}$$

$$\begin{aligned}
Y_{s,t} &= \text{man-hours per maintenance action, squadron s, month t} \\
X_{1,s,t} &= \text{type equipment code} \\
X_{2,s,t} &= \text{average aircraft hours in service} \\
X_{3,s,t} &= \text{location} \\
X_{4,s,t} &= \text{months in squadron, median} \\
X_{5,s,t} &= \text{deployment status} \\
\varepsilon_{s,t} &= \text{residual} \\
k &= \text{number of variables} \\
s &= \text{squadron} \\
t &= \text{month}
\end{aligned}$$

A summary of the S-Plus output is shown in **Error! Reference source not found.**. The stepwise regression identifies the most significant terms with respect to man-hours per maintenance action: *type equipment code, average aircraft hours in service, location, months in squadron* (median), and *deployment.*

Since we have transformed the response variable with the natural log function, this model explains approximately 26.4% of the variability of the natural log of the response variable $\ln(Y_{s,t})$. To find the relevant value of R^2 that applies to the response variable directly, we convert the estimates of $\ln(Y_{s,t})$ to those representing $Y_{s,t}$ with the exponential function and re-calculate R^2; this procedure results in an R^2 of 0.18. The F-statistic indicates that the model is significant when compared to the intercept-only model.

From the coefficients of the regression model, we can interpret the individual variable effects on the natural logarithm of the performance metric *man hours per maintenance action*. Negative coefficients of numerical variables indicate that predicted values of *MMHperMA* are higher for the specified level of the variable than for the level not shown. For example, expected values of *MMHperMA* decrease for increasing values of TimeInSqdnMed (median of *months in squadron*), which is the intuitive result. Coefficients for categorical variables are somewhat harder to interpret. We use analysis of variance (ANOVA) as a way of measuring the ratio of variability of a specific factor to the unexplained variability (noise); the p-values of the ANOVA table tell us the significance of the categorical term as a whole. For example, the *TEC* term is significant at the 0.05 level.

```
Call: lm(formula = log(MMHperMA) ~ TEC + AvgAircraftHrsInSvc + Loc +
TimeInSqdnMed + Deployment, data = A, na.action = na.exclude)
Residuals:
     Min      1Q  Median     3Q    Max
 -0.7744 -0.1301 0.01057 0.1169 0.6243

Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  1.1199  0.2008     5.5780  0.0000

            TECAMAF  0.0281  0.0670     0.4194  0.6754
            TECAMAG  0.1711  0.0791     2.1622  0.0318
AvgAircraftHrsInSvc  0.0000  0.0000     1.6090  0.1092
                Loc  0.2089  0.0364     5.7472  0.0000
      TimeInSqdnMed -0.0203  0.0043    -4.7092  0.0000
      DeploymentUDP -0.0697  0.0429    -1.6253  0.1057
      DeploymentCVN  0.1934  0.1025     1.8868  0.0606
     DeploymentIRAQ  0.1214  0.1568     0.7741  0.4398

Residual standard error: 0.2105 on 201 degrees of freedom
Multiple R-Squared: 0.2642
F-statistic: 9.021 on 8 and 201 degrees of freedom, the p-value is 1.464e-010

Analysis of Variance Table

Response: log(MMHperMA)

Terms added sequentially (first to last)
                     Df Sum of Sq  Mean Sq  F Value      Pr(F)
                TEC   2  0.286042 0.143021  3.22892 0.04166326
AvgAircraftHrsInSvc   1  0.137936 0.137936  3.11411 0.07913569
                Loc   1  1.365617 1.365617 30.83090 0.00000009
      TimeInSqdnMed   1  1.098606 1.098606 24.80272 0.00000136
         Deployment   3  0.308534 0.102845  2.32188 0.07634081
          Residuals 201  8.903050 0.044294
```

Figure 23 Stepwise Variable Selection, S-Plus Report.

We conduct residual analysis on this reduced model to check the assumptions of linear regression. Appendix F shows three residual plots for this regression: the residuals against the fitted values, the responses against the fitted values, and the normal quantile-quantile (QQ) plot of the residuals. As seen by these plots, the residuals appear to have fairly constant variance and normal distribution, their variance appears to be constant, and they appear to be independent of the fitted values.

3. Unexplained Variability in the Performance Measure

As noted above, this model explains only 18 percent of the variability of the *man-hours per maintenance action* performance measure. In its current form, we have left the *organization* term out of the model, suggesting that the model applies to all squadrons. We check the distribution of the residuals by squadron to know whether this is a valid conclusion. This plot is shown in Figure 24 .

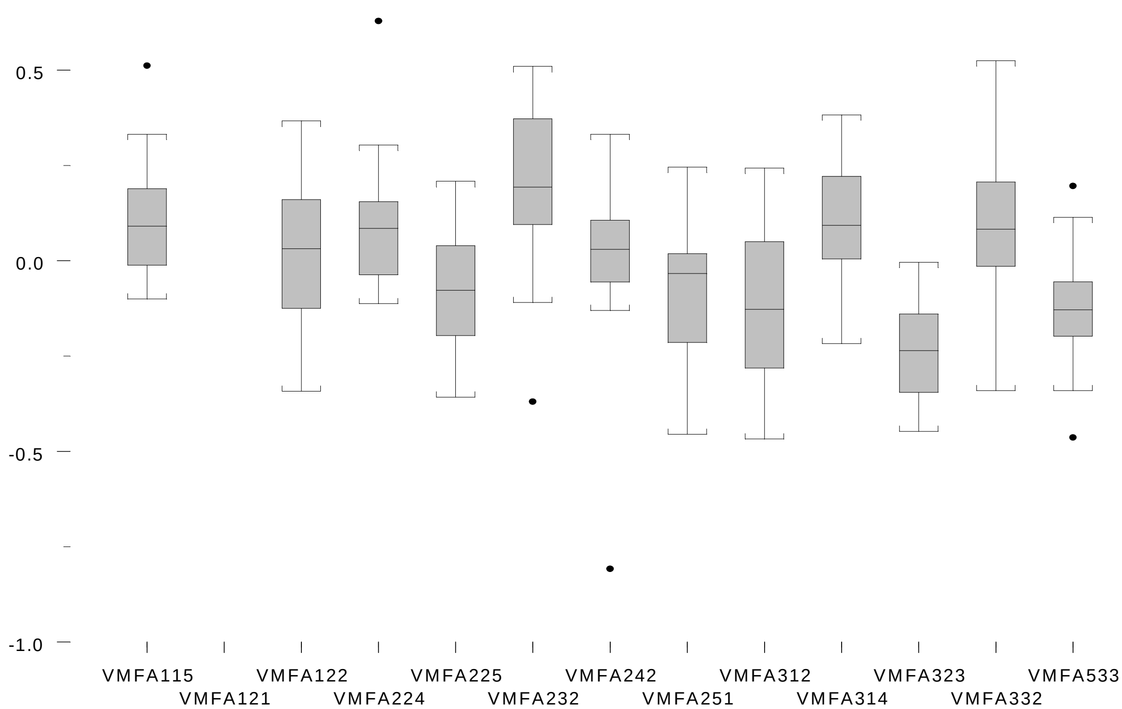

Figure 24 Boxplots of Residuals Grouped by Squadron, Stepwise Reduction Model.
The box represents all data between the 25th and 75th percentiles. The line inside the box represents the median of the distribution. The vertical lines that extend above and below the box represent the range of data; dots outside these ranges represent outliers.

The plot indicates that the residuals are not evenly distributed among the squadrons. The model tends to under-predict *MMHperMA* for VMFA232, for example, and over-predict for VMFA323. We conclude, therefore, that there is variability in the residuals that is attributed to squadron characteristics that we have not accounted for with this model.

We measure the additional information carried by the *organization* term by including the term and fitting a new model. The ANOVA table from the output is shown in Figure 25 .

```
       *** Linear Model ***

Call: lm(formula = log(MMHperMA) ~ AvgAircraftHrsInSvc + TimeInSqdnMed +
Deployment + Org, data = A, na.action = na.exclude)
Residuals:
     Min      1Q     Median      3Q    Max
 -0.7842 -0.1022 -0.0007759 0.1025 0.5435

Coefficients:
                      Value Std. Error t value Pr(>|t|)



        (Intercept)  1.0106  0.2628     3.8456  0.0002
AvgAircraftHrsInSvc  0.0000  0.0000     0.7351  0.4631
      TimeInSqdnMed -0.0067  0.0034    -1.9337  0.0544
      DeploymentUDP -0.0585  0.0353    -1.6577  0.0988
      DeploymentCVN  0.1494  0.0532     2.8079  0.0054
     DeploymentIRAQ -0.1167  0.0866    -1.3475  0.1792
         OrgVMFA122 -0.1439  0.0755    -1.9054  0.0580
         OrgVMFA224  0.1033  0.0966     1.0688  0.2863
         OrgVMFA225  0.1367  0.1366     1.0007  0.3181
         OrgVMFA232  0.2641  0.0873     3.0261  0.0028
         OrgVMFA242  0.1941  0.1057     1.8366  0.0676
         OrgVMFA251 -0.2530  0.0973    -2.5988  0.0100
         OrgVMFA312 -0.2043  0.0589    -3.4655  0.0006
         OrgVMFA314  0.1929  0.1307     1.4761  0.1413
         OrgVMFA323 -0.1907  0.0899    -2.1200  0.0351
         OrgVMFA332  0.1114  0.1144     0.9737  0.3312
         OrgVMFA533 -0.1063  0.1010    -1.0524  0.2938

Residual standard error: 0.1835 on 223 degrees of freedom
Multiple R-Squared: 0.4887
F-statistic: 13.32 on 16 and 223 degrees of freedom, the p-value is 0
163 observations deleted due to missing values
```

Figure 25 Reduced Model, Organization Term Included, S-Plus Report

The R^2 value has increased to 0.4887, which is double the explanatory power than the model without the *organization* term. We use ANOVA to test the significance of the added term. The results of the ANOVA test, shown in Figure 26 , indicate that the model with the *organization* term is significantly better at explaining variability of *man-hours per maintenance action* than the model without the organization term.

Note that *TEC* and *Location* have been removed from the model before inclusion of the *organization* term; this is because these variables are uniquely determined by the *organization* variable. If we include all three terms, we face singularity in the design matrix used to calculate the least squares solution.

```
> anova(lm3,lm3plusOrg)
Analysis of Variance Table

Response: ln(MMHperMA)
```

Terms	Resid. Df	RSS	Test	Df	Sum of Sq	F Value	Pr(F)
1 TEC + AvgAircraftHrsInSvc + Loc + TimeInSqdnMed + Deployment	231	11.21171					
2 AvgAircraftHrsInSvc + TimeInSqdnMed + Deployment + Org	223	7.50948	1 vs. 2	8	3.702232	13.74259	3.330669e-016

Figure 26 ANOVA Test for Significance of Added *Organization* Term.

4. Measuring Tech Rep Effects with ELAR

We want to know if the volume of tech rep activity affects the performance of the squadrons. We use the number of ELAR records in a given month as a measure of tech rep activity. As observed in Section C of this chapter, users of ELAR have been regularly recording the squadron field only recently, giving us only several months of records to which we can attribute to a specific squadron. The method used above is applied to test if there is additional explanatory power when adding the ELAR term to the model. We test

$$H_0 : \ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \beta_6 X_{6,s,t} + \varepsilon_{s,t} \quad (4)$$

against the alternative

$$H_a : \ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \beta_6 X_{6,s,t} + \beta_7 X_{7,s,t} + \varepsilon_{s,t} \quad (5)$$

where

$Y_{s,t}$ = man-hours per maintenance action, squadron s, month t
$X_{1,s,t}$ = type equipment code
$X_{2,s,t}$ = upper quartile, months experience
$X_{3,s,t}$ = location
$X_{4,s,t}$ = median, months in squadron
$X_{5,s,t}$ = deployment status
$X_{6,s,t}$ = flight hours
$X_{7,s,t}$ = ELAR records
$\varepsilon_{s,t}$ = residual

We then use ANOVA to test for the difference between the two models. We further test for the individual affects of the various types of tech rep activities by counting ELAR records by problem type and giving each problem type its own term in the model. In this way we differentiate between the effects of training-related activities that precede aircraft malfunctions and those repair-related activities that follow aircraft malfunctions. With several years' worth of additional observations, entered regularly by all squadrons, we believe that the techniques employed here will be effective in identifying those areas where tech rep activity has improved maintenance performance.

5. Lag Effects

The various squadron characteristics that explain squadron performance might not immediately affect the performance metric. If we believe that some of the predictors exhibit a delayed effect on performance, then we lag those individual variables backward by the appropriate time interval. For our purposes we lag the response variable *man-hours per maintenance action* forward by one month, to check whether the explanatory variables have, in general, have a one-month delay until reflected in the performance measure. The resulting model, formally, is

$$\ln Y_{s,t+1} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + ... + \beta_k X_{k,s,t} + \varepsilon_{s,t} \quad (6)$$

which is equivalent to lagging the predictors backward a month:

$$\ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t-1} + \beta_2 X_{2,s,t-1} + ... + \beta_k X_{k,s,t-1} + \varepsilon_{s,t} \quad (7)$$

We are using the performance metric *man-hours per maintenance action* specifically because we believe that it is a leading, not a lagging, indicator. That is, we expect little delay between changes in squadron characteristics and the resultant change in the leading indicator. For this reason, we do not pursue the issue of lagging variables further in this analysis.

6. Time Effects

Although we normally consider the possibility of a time-of-year effect in a response variable as observed over the course of time, the performance variable in this case, *man-hours per maintenance action* should not be affected by the month or quarter during which it is measured. We can think of no reason why the squadron performance would fluctuate by quarter. The environmental changes experienced by Marine squadrons is affected more by the geographic location associated with their current operating base, whether at home base or deployed, than it is by the season. Furthermore, to detect monthly or quarterly effects, we need several years' worth of data. For these reasons, we do not include a month or quarter factor in the model.

The data for this analysis were collected as time series observations for each of the squadrons under investigation. Each record, therefore, has an associated month, quarter, and year. For time series data, we check for serial correlation of the residuals to ensure that we do not have time patterns in the residuals, indicating a time effect of some sort. Presence of serial correlation may cast doubt on the reliability of estimates derived from the fitted model. The Durbin-Watson test is a common test for detecting serial correlation of the residuals resulting from regression models. Draper and Smith [1981] provide a description of this test. We usually assume that the residuals from a linear model are independent and normally distributed, and that all serial correlations, $\rho_s = 0$. We test the null hypothesis $H_0 : \rho_s = 0$ against the alternative, $H_a : \rho_s = \rho^s$. We use the Durbin-Watson statistic,

$$dw = \frac{\sum_{t=1}^{n-1}(e_t - e_{t+1})^2}{\sum_{t=1}^{n}(e_t - \overline{e})^2}$$

to determine whether our residuals call for us to reject the null hypothesis. Since our data columns are observations which have been stacked by squadron, we "unstack" the data and treat each squadron separately as its own time series of observations with its own set of residuals. For each of these sets of residuals we form the Durbin-Watson statistic dw, and reject H_0 if dw is below a critical value obtained from tables such as those published in Draper and Smith [1981]. Use of these tables requires three parameters: the level of significance, the number of variables and the number of observations. In our case, for α = 0.05, n=20, and k=4, we obtain a critical value of dw=1.70. For a two-sided test against alternatives $\rho \neq 0$, if $dw < dw_{crit}$ or if $4 - dw < dw_{crit}$, we reject H_0 at level 2α. We calculate the statistic for each of the squadrons, and the results are as follows:

	dw	1-dw	n
[1,]	1.679851	2.320149	20
[2,]	1.618424	2.381576	20
[3,]	1.558493	2.441507	20
[4,]	2.140955	1.859045	20
[5,]	1.318383	2.681617	20
[6,]	1.535749	2.464251	20
[7,]	1.636940	2.363060	20
[8,]	2.159661	1.840339	20
[9,]	1.933646	2.066354	20
[10,]	1.388049	2.611951	20
[11,]	1.316829	2.683171	20
[12,]	2.153625	1.846375	20

Figure 27 Durbin-Watson Test of the Residuals
dw: the vector of 12 Durbin-Watson statistics calculated from the residuals of each squadron's observations. VMFA-121 has been omitted.
n: the number of observations for each squadron.
4-dw: used to test the lower side of the 2-sided Durbin-Watson test.

For α=0.025, we expect approximately 5% of our 2-sided tests to reject H_0. In our case, we see that eight of the twelve squadrons have resulted in rejection of the null, which leads us to believe that we have some presence of autocorrelation of the residuals.

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IV. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

The primary objective of this thesis is to identify F/A-18 squadron characteristics that are important predictors of maintenance performance. A secondary objective is to draw insights on performance from data collected by NATEC, in ELAR, on the utilization of engineering and technical services. The two-year time frame of our study was a limiting factor in discerning relationships for two reasons: it necessarily restricted the levels of change that were possible in the squadron attributes that were measured; and in the case of ELAR, it implied that the available data represented the “learning curve” of the system. Nonetheless, our analysis should provide a useful template for future studies with longer time series and with data of higher quality.

In the following subsections we address the five research questions that we posed in Chapter 1.

1. Significant Variables

Which squadron characteristics have a detectable contribution to the variability of the performance measure *man-hours per maintenance action*? From those variables included in the model selection process, five are found to be statistically significant in explaining at least some of the variability of the performance metric of this study, *man-hours per maintenance action*:

- Type Equipment Code
- Average aircraft hours in service
- Location
- Median, months in squadron
- Deployment status

The linear model including these variables explains approximately 28 percent of the variability of the natural logarithm of *man-hours per maintenance action*. We used a logarithm transformation to better meet the assumptions of a normal, linear model. For this study, only 20 monthly observations for each of the thirteen U.S.-based active duty Marine Corps F/A-18 squadrons were complete with no missing values.

2. Squadron Differences

How much additional variability is explained by the squadron that is not accounted for by the squadron characteristics already considered? To answer this question, we tested for a significant difference between two models: one without the *organization* term, and the same model with an *organization* term added. We find that by including *organization* in the model, we are defining a different fit for each squadron. We gain significant additional predictive power with the inclusion of this term. The value of R^2 is improved from approximately 0.24 to 0.48, which tells us that the squadrons are different in ways for which our variables do not account. There is important information in both models. Without the *organization* term, we have a model that applies to all squadrons. This model would therefore, presumably, apply to any squadron if its characteristics were similar in general to those that formed the model. If we instead allow for a different fit for each squadron, by adding the *organization* term, we obtain a model that can be used to predict changes in *man-hours per maintenance action* as conditions change within a particular squadron.

3. Time Effects and Autocorrelation

Is there a time-of-year effect for the performance of the squadrons? We do not find the quarter term to be significant in the model, so we conclude that all quarters are essentially the same. However, this study is limited to 20 months of complete observations, which is a relatively small set of data to test for a quarterly effect. Through employment of the Durbin-Watson test, we do detect a slight correlation of the residuals, suggesting that the residuals are not independent. There is a temporal structure, although slight, which could be handled with a generalized least squares approach.

B. RECOMMENDATIONS

1. Additional Variables

What additional metrics not currently available would most likely be useful in an explanatory model of maintenance performance? Our methods depend on the aggregation of data by month and on the use of aviation maintenance metrics currently available from NALCOMIS. However, many metrics could be derived with direct access to the actual records in NALCOMIS. Since we are trying to measure maintainer capability, we would like to have as many metrics that quantify this capability as possible. Several of the metrics currently unavailable that would likely be useful are repeat discrepancy rate, the fix rate, and the maintenance efficiency rate. These metrics are recognized by Air Force maintenance analysts for their importance [AFLMA, 2001]. The repeat discrepancy rate gives an indication of those malfunctions that were thought to have been repaired but were not, in effect, repaired correctly. The fix rate is the ratio of critical discrepancies repaired to the total critical discrepancies received, where critical discrepancies are those that place the aircraft in a not-flyable status. The maintenance efficiency ratio is the maintenance actions completed as a percentage of those scheduled (in a given time period).

2. ETS Data Collection

What data collection methods, if any, would be likely to improve the ability of NATEC managers to correlate squadron characteristics to tech rep measures of performance? Our goal is to identify tech rep activity that correlates with measures of squadron performance. To achieve this goal, we need to link tech rep activity to the maintenance activity that the tech reps are assisting and to the performance measure that we are analyzing. To link the tech rep activity to the specific maintenance activity under investigation, we need a reliable (preferably automated) means of identifying specific repair actions with a tech rep. To that end, we need one-to-one relationships between the records in ELAR, or its equivalent, and those in NALCOMIS.

This can be achieved in several ways. The (ELAR) database could require that an accurate job control number (JCN) from the corresponding NALCOMIS record be entered into each ELAR record. The JCN is a unique number that would clearly identify the maintenance action to which the ELAR record applies. A more effective solution would be for NALCOMIS to integrate any tech rep activity directly with maintenance action. For instance, there is a non-mandatory (and therefore seldom-used) block on the maintenance action form (MAF) by which tech rep assistance can be identified. More effective, perhaps, would be to expand the capability of the MAF to allow for additional tech rep details, such as the name of the tech rep, the type of assistance rendered, the actual start time and end time of the tech rep action, and any other customer service-type information that could quickly be added at the data point-of-entry. Another alternative would be to require that the tech rep document his or her actions in NALCOMIS before the MAF can be approved by maintenance control supervisors.

3. Real-Time Maintenance Proficiency

A large part of the tech reps' value to the squadrons is in their training role. Tech reps fill the gaps between initial MOS training and formal follow-on school training that is not available to every maintainer. For that reason, there is a need to more accurately quantify the training level of the squadron in general and of each maintainer specifically. In other words, at any given time, we need to be able to obtain a picture of the training levels across a squadron's maintenance department. For aircrews, this is achieved through the use of a training and readiness (T&R) syllabus and through the correct demonstration, at regular intervals, of mission essential tasks. The maintainers need an analogous list of mission essential tasks, specific to their MOS's, which need to be performed at prescribed intervals to maintain proficiency and "currency." Each repair they perform, either on actual discrepancies or in a training setting, "updates" the currency of qualification in that specific area of repair. At any point in time, the commander (or NATEC) could see areas of maintenance training that have not been accomplished in some time (approaching expiration) and must therefore be addressed through training. In this way, limited tech rep resources could be dedicated to preemptive training in those skill areas deemed to be critical and fleeting, rather than always reacting to an actual aircraft malfunction that demands unscheduled maintenance.

C. OPPORTUNITIES FOR FURTHER STUDY

1. Analysis of NALCOMIS Records

Analysis of several years' of NALCOMIS data records, which would include millions of individual flight and maintenance records, would call for analytical techniques not addressed here. Algorithmic statistical methods, such as clustering, classification trees, and neural networks, could be employed to find patterns in the data, which might demonstrate better predictive performance than traditional regression methods. For instance, we could use these techniques to predict whether or not a maintenance action of a certain type will require technical assistance. Other large data sets, such as supply records, could be incorporated with similar techniques. For any of these techniques to be useful with respect to tech rep performance, for the reasons discussed in Section B.3 of this chapter, the records need to have some direct link to tech rep activity.

2. Survey of Tech Rep Customers

Current indicators of customer satisfaction are those comments obtained from users of tech rep services at the completion of a tech rep action. For reasons discussed in Chapter I, the users of tech rep assistance have every incentive to request continued ETS support, since they do not "pay" for that support. Customers are understandably reluctant, therefore, to submit comments that will jeopardize the continued availability of tech reps. If, on the other hand, the customers (squadrons) are forced to make tradeoff decisions regarding resources, we might see a different picture. One way to obtain a more objective input would be to provide squadron commanders a fictitious "budget" that can be allocated towards those resources available to them but that they do not normally have to pay for: additional fuel, flight hours, personnel, repair parts and consumables, and technical services. In this light we could learn the true importance of technical services to those that have many other requirements as well.

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APPENDIX A
MISSION ESSENTIAL SUBSYSTEMS MATRIX, F/A-18

OPNAVINST 5442.4M
17 OCT 1990

F/A-18A/B/C/D
TYPE EQUIPMENT CODES: AMAA/AMAE/AMAF/AMAG

Do not assign an EOC code if all equipment is operational. The aircraft is OPC.

Assign alpha character (B) of the EOC code when the following system(s) are inoperative. The aircraft is FMC, M or S.

AUTOMATIC DIRECTION FINDER SET	
CLOCK	
EXTERNAL POWER SYSTEM	
MAGNETIC COMPASS (AQU-3/A)	
STRIKE CAMERA SYSTEM	(NOTE 1)
VIDEO TAPE RECORDER	(NOTE 1)

Assign alpha character (C) of the EOC code when the following system(s) are inoperative preventing the escort/strike mission. The aircraft is not capable of independent detection and destruction of aircraft/missiles under all-weather conditions or providing protective escort for strike and support forces using all air-to-air weapons in a multi-threat ECM environment. The aircraft is PMC, M or S.

LAU-116	(NOTE 1)
LAU-117	(NOTE 1)
MISSILE ILLUMINATION GROUP SPARROW	
SPARROW MISSILE EJECTOR LAUNCHER	

Assign alpha character (D) of the EOC code when the following system(s) are inoperative preventing the strike mission. The aircraft is not capable of conducting interdiction or war-at-sea missions using all weapons and delivery modes compatible with aircraft regardless of terrain, weather or enemy defenses. The aircraft is PMC, M or S.

AMAC SYSTEM	(NOTES 1,2)
WEAPON CONTROL (HUD, MULTIPURPOSE DISPLAY GROUP)	(NOTE 3)

Assign alpha character (J) of the EOC code when the following system(s) are inoperative preventing the visual attack mission. The aircraft is not capable of conducting missions under VMC, using system deliveries of conventional ordnance, conducting anti-radiation missile strike support, close air support for friendly forces with forward air controller. The aircraft is PMC, M or S.

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Figure A-1. Chief of Naval Operations Instruction 5442.4M (OPNAVINST 5442.4M). (1992). Aircraft material condition definitions, mission-essential subsystems matrices (MESMS), and Mission Descriptions. 01 July 1992.

F/A-18A/B/C/D/ (cont)

ACM (AWG-25)(HARM)	(NOTE 1)
ANTI-G SUIT PRESSURE	
ARMAMENT CONTROL PROC SET	
CENTERLINE PYLON (SUU-62)	(NOTE 1)
CHAFF COUNTERMEASURES SET (ALE-39)	(NOTE 1)
COUNTERMEASURES SET (ALQ-126 OR ALQ-165)	(NOTE 1)
DATA STORAGE UNIT	
DIGITAL MAP	
EW THREAT DISPLAY	
FLIR POD AND ADAPTER	(NOTE 1)
HAVEQUICK/SINCGARS (ARC-182)	
HORIZONTAL INDICATOR	(NOTE 4)
LASER SPOT TRACKER AND ADAPTER	(NOTE 1)
LASER TARGET DESIGNATOR/RANGER	(NOTE 1)
NAVIGATION FLIR	
NIGHT VISION GOGGLES	
PALLETIZED GUN SYSTEM (M61A1)	
RADAR LIQUID COOLING SYSTEM	
RADAR SET (APG-65)	(NOTE 4)
RADAR WARNING RECEIVER (ALR-67)	(NOTE 1)
SELECTIVE STORES JETTISON SYSTEM	
SIDEWINDER MISSILE SYSTEM	
SIDEWINDER LAUNCHERS (LAU-7A)	(NOTE 1)
THREAT WARNING LIGHT DISPLAY GROUP	
WEAPON RELEASE RACKS (BRU-32/A or BRU-32A/A)	(NOTE 1)
WEAPON SYSTEM CONTROL FUNCTION (HOTAS)	(NOTE 4)
WING PYLONS (SUU-63)	(NOTE 1)

Assign alpha character (K) of the EOC code when the following system(s) are inoperative preventing the expanded mobility mission. The aircraft is not capable of safe movement on and off CV/SATs during day, night and inclement weather conditions, conducting independent navigation, using encrypted radio voice communications and IFF, or in-flight refueling (receive). The aircraft is PMC, M or S.

AIR REFUELING PROBE	
AIR REFUELING PROBE FLOOD LIGHT	
ANGLE-OF-ATTACK SYSTEM AND INDEX LIGHTS	
APPROACH POWER COMPENSATOR SYSTEM	
BOARDING LADDER DRAG BRACE	
CATAPULT SYSTEM	
EMERGENCY JETTISON SYSTEM	
ILS RECEIVER/DECODER (ARA-63)	(NOTE 5)

Figure A-1. Chief of Naval Operations Instruction 5442.4M (OPNAVINST 5442.4M). (1992). Aircraft material condition definitions, mission-essential subsystems matrices (MESMS), and Mission Descriptions. 01 July 1992.

F/A-18A/B/C/D (CONT)

MISSION COMPUTERS (BOTH REQUIRED)	
RADAR BEACON (APN-202) AND RT (1028/APN-202)	(NOTE 5)
RECEIVER TRANSMITTER PROCESSOR (RT-1379/ASW)	(NOTE 5)
SECONDARY POWER SUPPLY (APU)	
SECURE IFF (KIT 1A)(MODE 4)	(NOTE 1)
SECURE VOICE (KY-58)	(NOTE 1)
WING FOLD	

Assign alpha character (L) of the EOC code when the following system(s) are inoperative preventing the IMC flight mission. The aircraft is not capable of day or night IMC field flight operations with necessary communications, IFF, navigation, flight and safety systems required by applicable NATOPS and FAA regulations. The aircraft is PMC, M or S.

ALTIMETER, ELECTRONIC (APN-194(V))	
ENGINE ANTI-ICE SYSTEM	
EXTERIOR LIGHTING (POSITION AND FORMATION)	(NOTE 6)
IFF TRANSPONDER (APX-100(V))	
INTERIOR LIGHTING	
MISSION COMPUTERS (AYK-14)(MC1 REQUIRED)	
PITOT/ANGLE-OF-ATTACK PROBE HEATER SYSTEM	
TACTICAL NAVIGATION SET (ARN-118(V))	
TAXI LIGHT	
UP FRONT CONTROL	
WINDSHIELD ANTI-ICE AND RAIN REMOVAL	
WHEEL ANTI-SKID CONTROL SYSTEM	

Assign alpha character (Z) of the EOC code when the following system(s)/condition(s) prevent the aircraft from being safely flyable. The aircraft is not capable of day, field flight operations under VMC with two-way radio communication and necessary aircraft and crew safety provisions. The aircraft is NMC, M or S.

AIR CONDITIONING/PRESSURIZATION
AIRFRAME
BOMBING NAVIGATION (INS)
CSC
DECELERATION EQUIPMENT/DROGUE PARACHUTE
ELECTRICAL SYSTEMS
EMERGENCY/PARKING BRAKE
EMERGENCY EQUIPMENT
EMERGENCY RADIO

Figure A-1. Chief of Naval Operations Instruction 5442.4M (OPNAVINST 5442.4M). (1992). Aircraft material condition definitions, mission-essential subsystems matrices (MESMS), and Mission Descriptions. 01 July 1992.

F/A-18A/B/C/D (cont)

EMI PROTECTION DEVICES	(NOTE 7)
ENGINES	
EXPLOSIVE DEVICES	
FLIGHT CONTROLS	
FLIGHT REFERENCE	(NOTE 8)
FUEL SYSTEM (FUSELAGE AND WINGS)	
FUSELAGE COMPARTMENTS	
HYDRAULIC/PNEUMATIC SYSTEM	
ICS (REQUIRED IN F/A-18B AND F/A-18D)	
INSTRUMENTS/INSTRUMENT SYSTEM (WUC 51 SERIES)	(NOTE 9)
INTEGRATED GUIDANCE AND FLIGHT CONTROL (ASN-130 OR ASN-139)	
LANDING GEAR	
LIGHTING SYSTEMS (ANTI-COLLISION LIGHT)(2 MINIMUM)	
MAINTENANCE SIGNAL DATA RECORDER SET	
MISCELLANEOUS UTILITIES	
OXYGEN SYSTEMS/OBOGS	
POWER PLANT INSTALLATION	
STRAIN GAUGES	(NOTE 10)
UHF COMMUNICATION SYSTEMS (1 REQUIRED)	
WEAPON CONTROL (HEAD-UP DISPLAY, MULTIPURPOSE DISPLAY GROUP)	(NOTE 3)
WEAPON DELIVERY	
CONDITIONAL INSPECTION	(NOTE 11)
ENGINE INSPECTION	(NOTE 11)
PHASE INSPECTION	(NOTE 11)
SPECIAL INSPECTION	(NOTE 11)
TECHNICAL DIRECTIVE COMPLIANCE	(NOTE 11)

NOTES:

1. WHEN THE EQUIPMENT IS INSTALLED, REPORT ON THE COMPLETE SYSTEM. WHEN THE EQUIPMENT IS NOT INSTALLED, REPORT ON THE WIRING AND PLUMBING ONLY.
2. NOT APPLICABLE TO VMFA SQUADRONS UNLESS ASSIGNED TO CVW.
3. HUD, LEFT AND RIGHT DDI, KI REQUIRED FOR MISSIONS A, B, C AND D. HUD AND LEFT DDI REQUIRED FOR MISSIONS J, K AND L.
4. ALL AIR-TO-AIR, ACM, AND AIR-TO-GROUND MODES REQUIRED.
5. EITHER: RADAR BEACON (APN-202 AND RT (1028/APN-202), OR ILS RECEIVER/DECODER (ARA-63) AND RECEIVER TRANSMITTER PROCESSOR (RT-1379/ASW) REQUIRED.
6. ONLY REQUIRED TO BE CODED (L) IF LESS THAN TWO (2) POSITION LIGHTS AND THREE (3) FORMATION LIGHTS ARE OPERABLE ON EACH

Figure A-1. Chief of Naval Operations Instruction 5442.4M (OPNAVINST 5442.4M). (1992). Aircraft material condition definitions, mission-essential subsystems matrices (MESMS), and Mission Descriptions. 01 July 1992.

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F/A-18A/B/C/D (cont)

SIDE OF AIRCRAFT.

7. DUE TO THE RELATIONSHIP OF ELECTROMAGNETIC INTERFERENCE (EMI) TO SAFETY OF FLIGHT, MAINTENANCE OF ALL EMI PROTECTION DEVICES SHALL BE MAINTAINED WITHIN LIMITS SPECIFIED IN THE APPROPRIATE TECHNICAL MANUALS.

8. INCLUDES: AIR DATA COMPUTER EQUIPMENT, MAGNETIC AZIMUTH DETECTOR.

9. INCLUDES: PRESSURE ALTIMETER (BOTH STANDBY AND RESET MODES), AIRSPEED INDICATOR, ATTITUDE REFERENCE INDICATOR, VERTICAL SPEED INDICATOR.

10. EITHER THE PRIMARY OR THE BACKUP STRAIN GAUGE, LOCATED IN THE SEVEN STRAIN GAUGE LOCATIONS (WING ROOT, WING FOLD, FORWARD FUSELAGE, RIGHT HORIZONTAL TAIL, LEFT HORIZONTAL TAIL, RIGHT VERTICAL TAIL, LEFT VERTICAL TAIL) MUST BE OPERABLE.

11. AS APPLICABLE PER REFERENCE (c).

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Figure A-1. Chief of Naval Operations Instruction 5442.4M (OPNAVINST 5442.4M). (1992). Aircraft material condition definitions, mission-essential subsystems matrices (MESMS), and Mission Descriptions. 01 July 1992.

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APPENDIX B
DATABASE INTERFACES

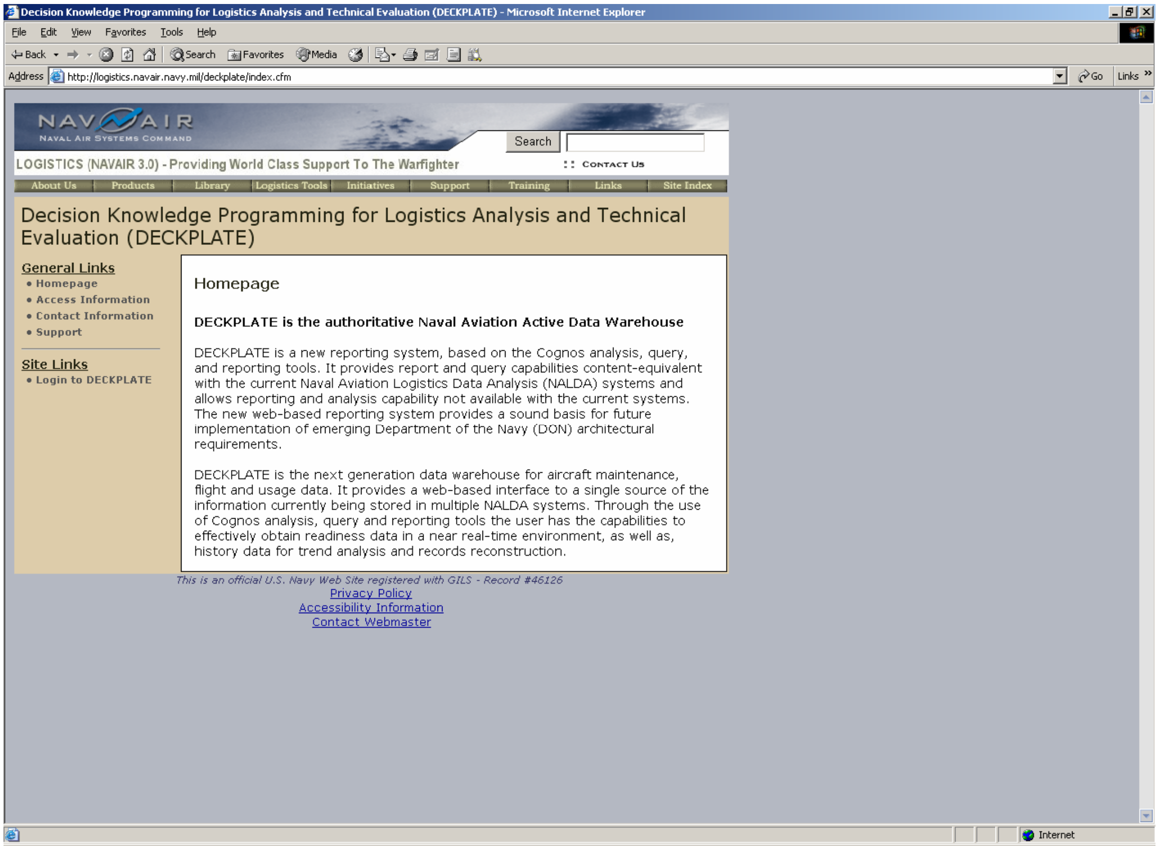

Figure B-1. Decision Knowledge Programming for Logistics Analysis and Technical Evaluation (DECKPLATE) user interface.

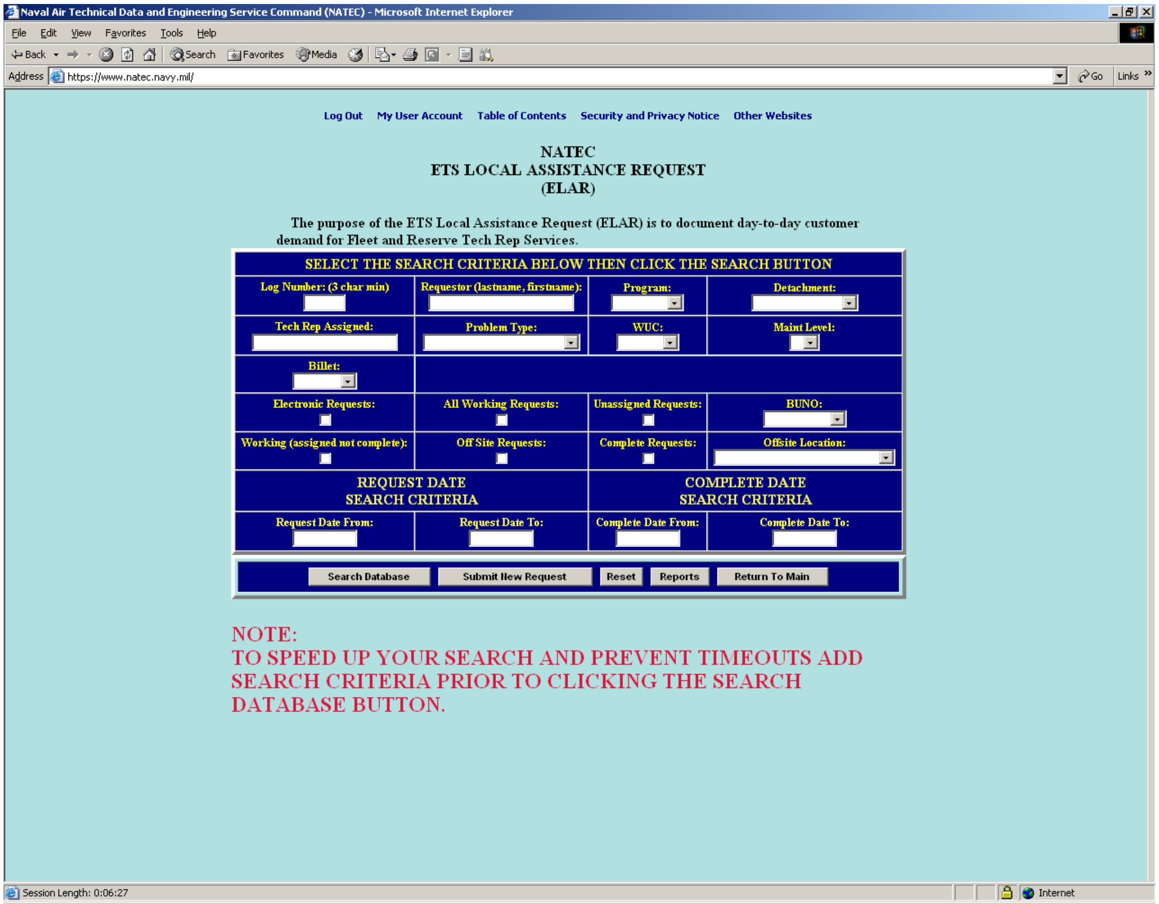

Figure B-2. NATEC ETS Local Assistance Request (ELAR) user interface for database query.

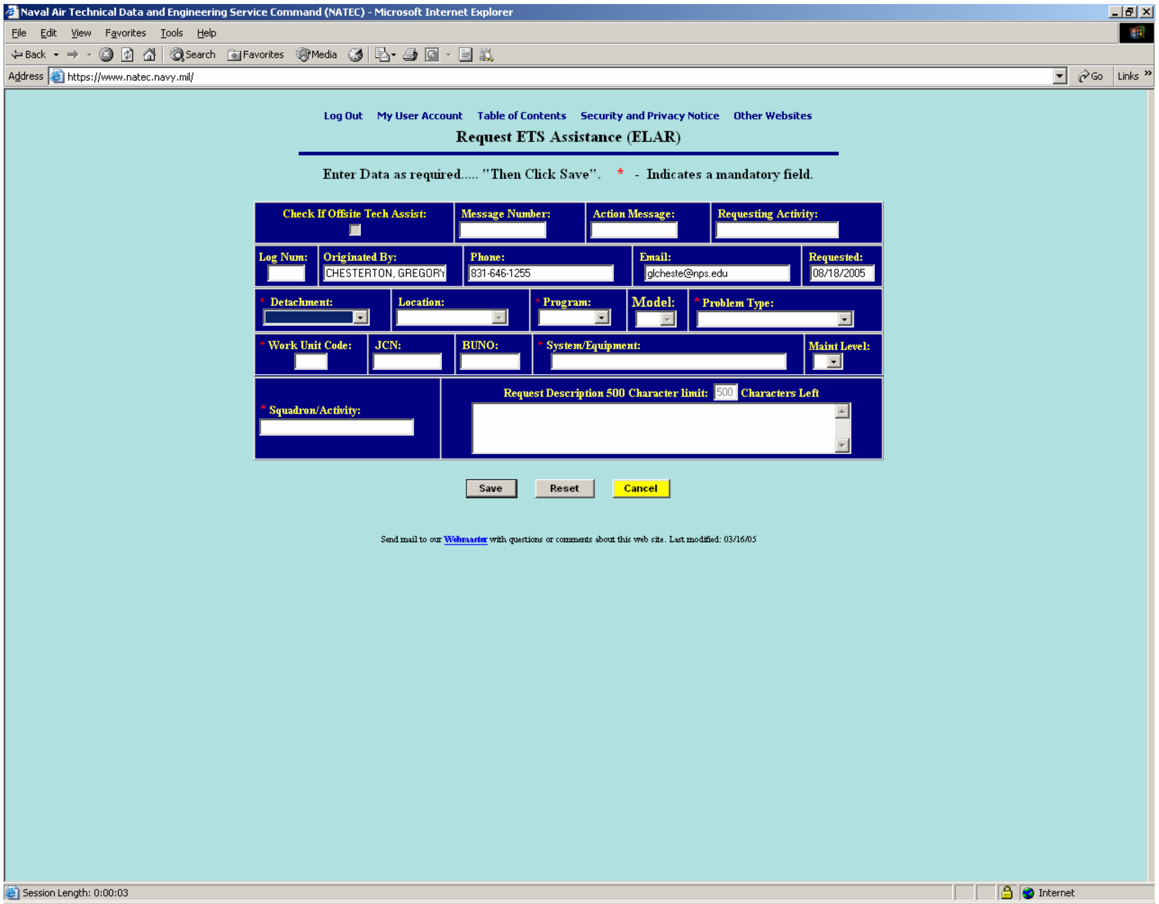

Figure B-3. NATEC ETS Local Assistance Request (ELAR) user interface for new request input.

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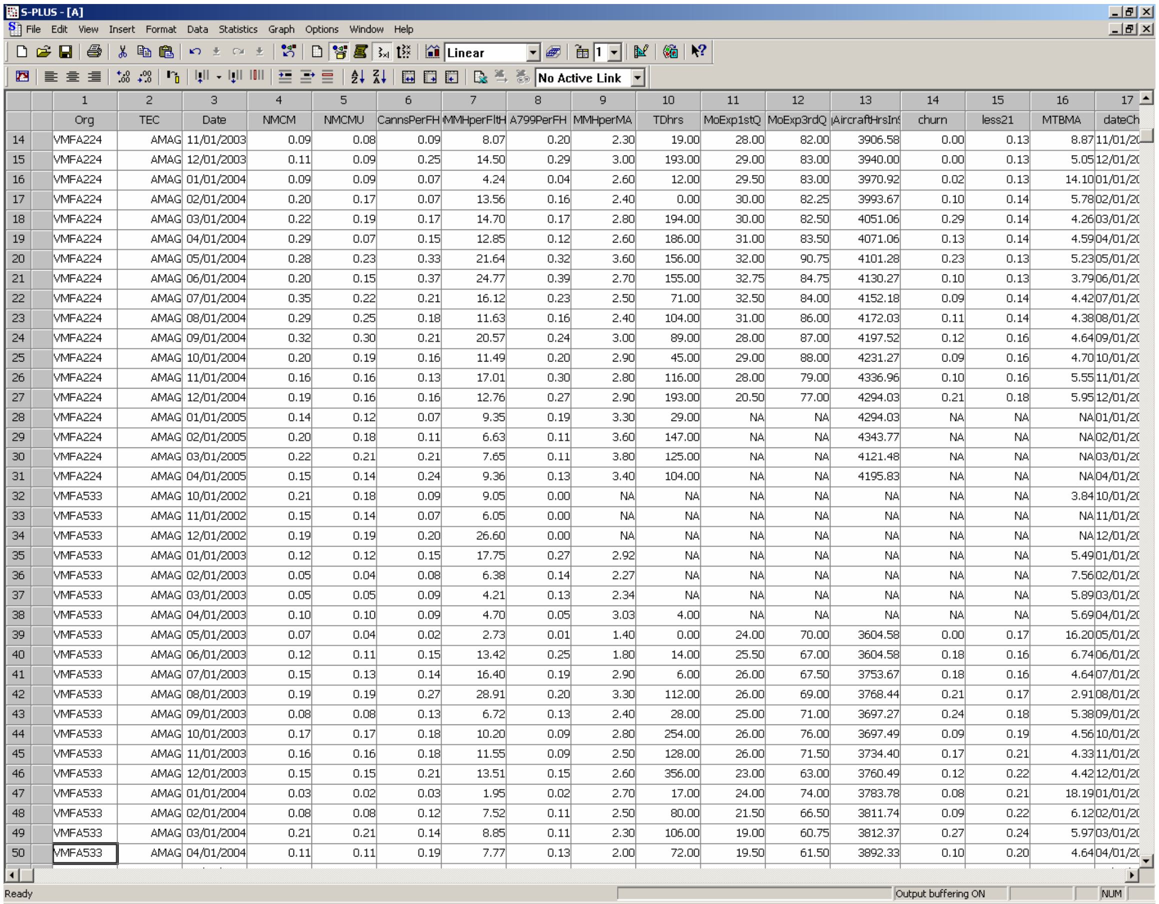
APPENDIX C
DATA COMPILATION



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Org	TEC	Date	NMCM	NMCMU	CannsPerFH	MMHperFltH	A799PerFH	MMHperMA	TDhrs	MoExp1stQ	MoExp3rdQ	AircraftHrsIn	churn	less21	MTBMA	dateCh
14	VMFA224	AMAG	11/01/2003	0.09	0.08	0.09	8.07	0.20	2.30	19.00	28.00	82.00	3906.58	0.00	0.13	8.87	11/01/20
15	VMFA224	AMAG	12/01/2003	0.11	0.09	0.25	14.50	0.29	3.00	193.00	29.00	83.00	3940.00	0.00	0.13	5.05	12/01/20
16	VMFA224	AMAG	01/01/2004	0.09	0.09	0.07	4.24	0.04	2.60	12.00	29.50	83.00	3970.92	0.02	0.13	14.10	01/01/20
17	VMFA224	AMAG	02/01/2004	0.20	0.17	0.07	13.56	0.16	2.40	0.00	30.00	82.25	3993.67	0.10	0.14	5.78	02/01/20
18	VMFA224	AMAG	03/01/2004	0.22	0.19	0.17	14.70	0.17	2.80	194.00	30.00	82.50	4051.06	0.29	0.14	4.26	03/01/20
19	VMFA224	AMAG	04/01/2004	0.29	0.07	0.15	12.85	0.12	2.60	186.00	31.00	83.50	4071.06	0.13	0.14	4.59	04/01/20
20	VMFA224	AMAG	05/01/2004	0.28	0.23	0.33	21.64	0.32	3.60	156.00	32.00	90.75	4101.28	0.23	0.13	5.23	05/01/20
21	VMFA224	AMAG	06/01/2004	0.20	0.15	0.37	24.77	0.39	2.70	155.00	32.75	84.75	4130.27	0.10	0.13	3.79	06/01/20
22	VMFA224	AMAG	07/01/2004	0.35	0.22	0.21	16.12	0.23	2.50	71.00	32.50	84.00	4152.18	0.09	0.14	4.42	07/01/20
23	VMFA224	AMAG	08/01/2004	0.29	0.25	0.18	11.63	0.16	2.40	104.00	31.00	86.00	4172.03	0.11	0.14	4.38	08/01/20
24	VMFA224	AMAG	09/01/2004	0.32	0.30	0.21	20.57	0.24	3.00	89.00	28.00	87.00	4197.52	0.12	0.16	4.64	09/01/20
25	VMFA224	AMAG	10/01/2004	0.20	0.19	0.16	11.49	0.20	2.90	45.00	29.00	88.00	4231.27	0.09	0.16	4.70	10/01/20
26	VMFA224	AMAG	11/01/2004	0.16	0.16	0.13	17.01	0.30	2.80	116.00	28.00	79.00	4336.96	0.10	0.16	5.55	11/01/20
27	VMFA224	AMAG	12/01/2004	0.19	0.16	0.16	12.76	0.27	2.90	193.00	20.50	77.00	4294.03	0.21	0.18	5.95	12/01/20
28	VMFA224	AMAG	01/01/2005	0.14	0.12	0.07	9.35	0.19	3.30	29.00	NA	NA	4294.03	NA	NA	NA	01/01/20
29	VMFA224	AMAG	02/01/2005	0.20	0.18	0.11	6.63	0.11	3.60	147.00	NA	NA	4343.77	NA	NA	NA	02/01/20
30	VMFA224	AMAG	03/01/2005	0.22	0.21	0.21	7.65	0.11	3.80	125.00	NA	NA	4121.48	NA	NA	NA	03/01/20
31	VMFA224	AMAG	04/01/2005	0.15	0.14	0.24	9.36	0.13	3.40	104.00	NA	NA	4195.83	NA	NA	NA	04/01/20
32	VMFA533	AMAG	10/01/2002	0.21	0.18	0.09	9.05	0.00	NA	NA	NA	NA	NA	NA	NA	3.84	10/01/20
33	VMFA533	AMAG	11/01/2002	0.15	0.14	0.07	6.05	0.00	NA	NA	NA	NA	NA	NA	NA	NA	11/01/20
34	VMFA533	AMAG	12/01/2002	0.19	0.19	0.20	26.60	0.00	NA	NA	NA	NA	NA	NA	NA	NA	12/01/20
35	VMFA533	AMAG	01/01/2003	0.12	0.12	0.15	17.75	0.27	2.92	NA	NA	NA	NA	NA	NA	5.49	01/01/20
36	VMFA533	AMAG	02/01/2003	0.05	0.04	0.08	6.38	0.14	2.27	NA	NA	NA	NA	NA	NA	7.56	02/01/20
37	VMFA533	AMAG	03/01/2003	0.05	0.05	0.09	4.21	0.13	2.34	NA	NA	NA	NA	NA	NA	5.89	03/01/20
38	VMFA533	AMAG	04/01/2003	0.10	0.10	0.09	4.70	0.05	3.03	4.00	NA	NA	NA	NA	NA	5.69	04/01/20
39	VMFA533	AMAG	05/01/2003	0.07	0.04	0.02	2.73	0.01	1.40	0.00	24.00	70.00	3604.58	0.00	0.17	16.20	05/01/20
40	VMFA533	AMAG	06/01/2003	0.12	0.11	0.15	13.42	0.25	1.80	14.00	25.50	67.00	3604.58	0.18	0.16	6.74	06/01/20
41	VMFA533	AMAG	07/01/2003	0.15	0.13	0.14	16.40	0.19	2.90	6.00	26.00	67.50	3753.67	0.18	0.16	4.64	07/01/20
42	VMFA533	AMAG	08/01/2003	0.19	0.19	0.27	28.91	0.20	3.30	112.00	26.00	69.00	3768.44	0.21	0.17	2.91	08/01/20
43	VMFA533	AMAG	09/01/2003	0.08	0.08	0.13	6.72	0.13	2.40	28.00	25.00	71.00	3697.27	0.24	0.18	5.38	09/01/20
44	VMFA533	AMAG	10/01/2003	0.17	0.17	0.18	10.20	0.09	2.80	254.00	26.00	76.00	3697.49	0.09	0.19	4.56	10/01/20
45	VMFA533	AMAG	11/01/2003	0.16	0.16	0.18	11.55	0.09	2.50	128.00	26.00	71.50	3734.40	0.17	0.21	4.33	11/01/20
46	VMFA533	AMAG	12/01/2003	0.15	0.15	0.21	13.51	0.15	2.60	356.00	23.00	63.00	3760.49	0.12	0.22	4.42	12/01/20
47	VMFA533	AMAG	01/01/2004	0.03	0.02	0.03	1.95	0.02	2.70	17.00	24.00	74.00	3783.78	0.08	0.21	18.19	01/01/20
48	VMFA533	AMAG	02/01/2004	0.08	0.08	0.12	7.52	0.11	2.50	80.00	21.50	66.50	3811.74	0.09	0.22	6.12	02/01/20
49	VMFA533	AMAG	03/01/2004	0.21	0.21	0.14	8.85	0.11	2.30	106.00	19.00	60.75	3812.37	0.27	0.24	5.97	03/01/20
50	VMFA533	AMAG	04/01/2004	0.11	0.11	0.19	7.77	0.13	2.00	72.00	19.50	61.50	3892.33	0.10	0.20	4.64	04/01/20

Figure C-1. S-Plus dataframe used for data compilation.

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APPENDIX D
PAIRWISE SCATTERPLOTS

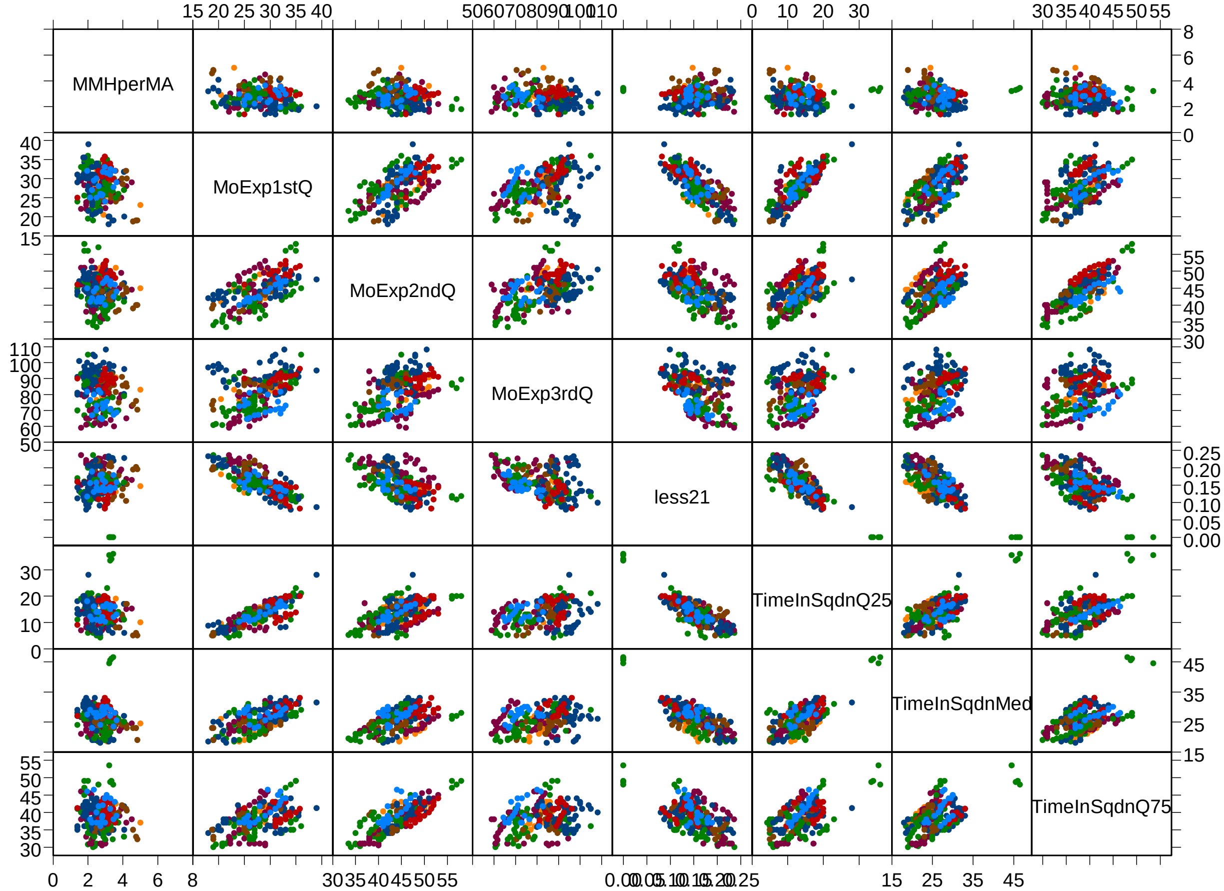

Figure D-1. MMHperMA and Personnel Factors Pairwise Scatter Plots. Each squadron's data is indicated with its own color shading.

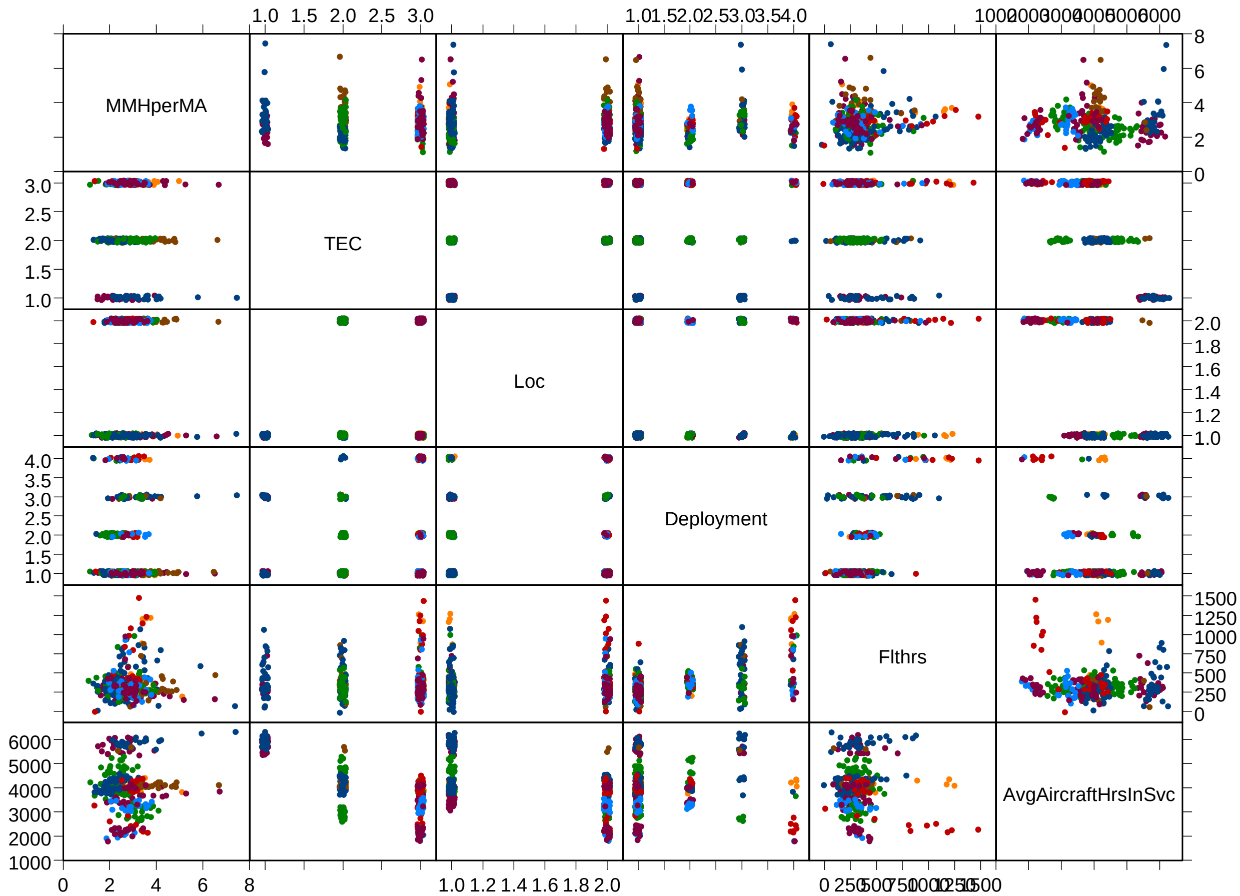

Figure D-2. MMHperMA and Inventory and Operational Factors Pairwise Scatter Plots. Each squadron's data is indicated with its own color shading.

APPENDIX E
FULL MODEL WITH NATURAL LOG TRANSFORMATION OF RESPONSE VARIABLE

$$\ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \beta_6 X_{6,s,t} + \beta_7 X_{7,s,t} + \beta_8 X_{8,s,t} + \beta_9 X_{9,s,t} + \beta_{10} X_{10,s,t} + \beta_{11} X_{11,s,t} + \varepsilon_{s,t}$$

$Y_{s,t}$ = man-hours per maintenance action, squadron s, month t
$X_{1,s,t}$ = type equipment code
$X_{2,s,t}$ = first quartile, months experience
$X_{3,s,t}$ = third quartile, months experience
$X_{4,s,t}$ = average aircraft hours in service
$X_{5,s,t}$ = turnover
$X_{6,s,t}$ = location
$X_{7,s,t}$ = first quartile, months in squadron
$X_{8,s,t}$ = second quartile, months in squadron
$X_{9,s,t}$ = third quartile, months in squadron
$X_{10,s,t}$ = deployment
$X_{11,s,t}$ = flight hours
$\varepsilon_{s,t}$ = residual
k = number of variables
s = squadron
t = month

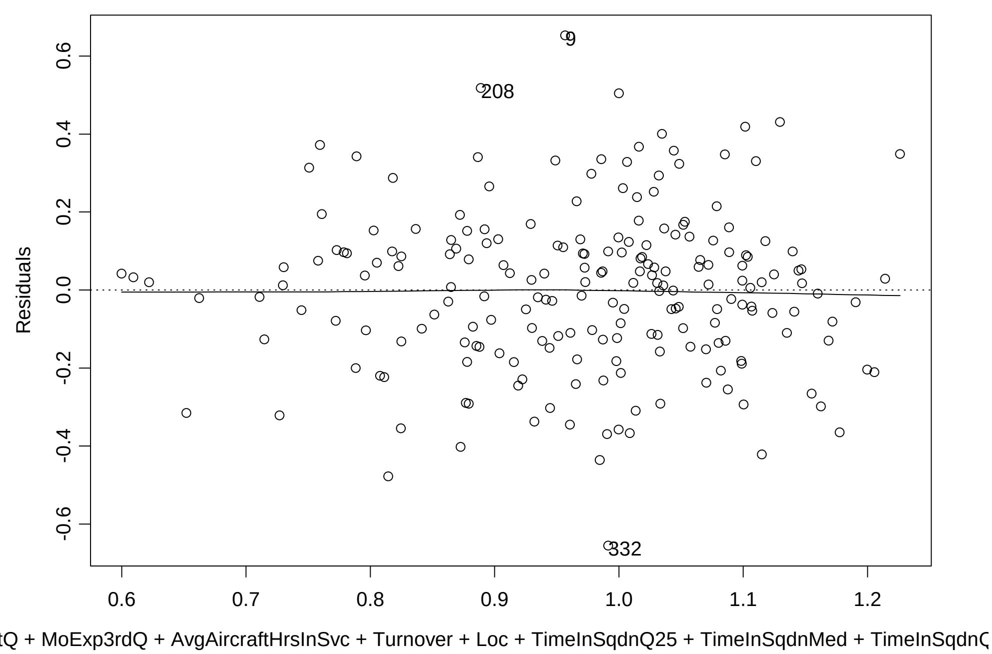

Figure E-1. Full Model and Plot of Residuals vs Fitted Values.

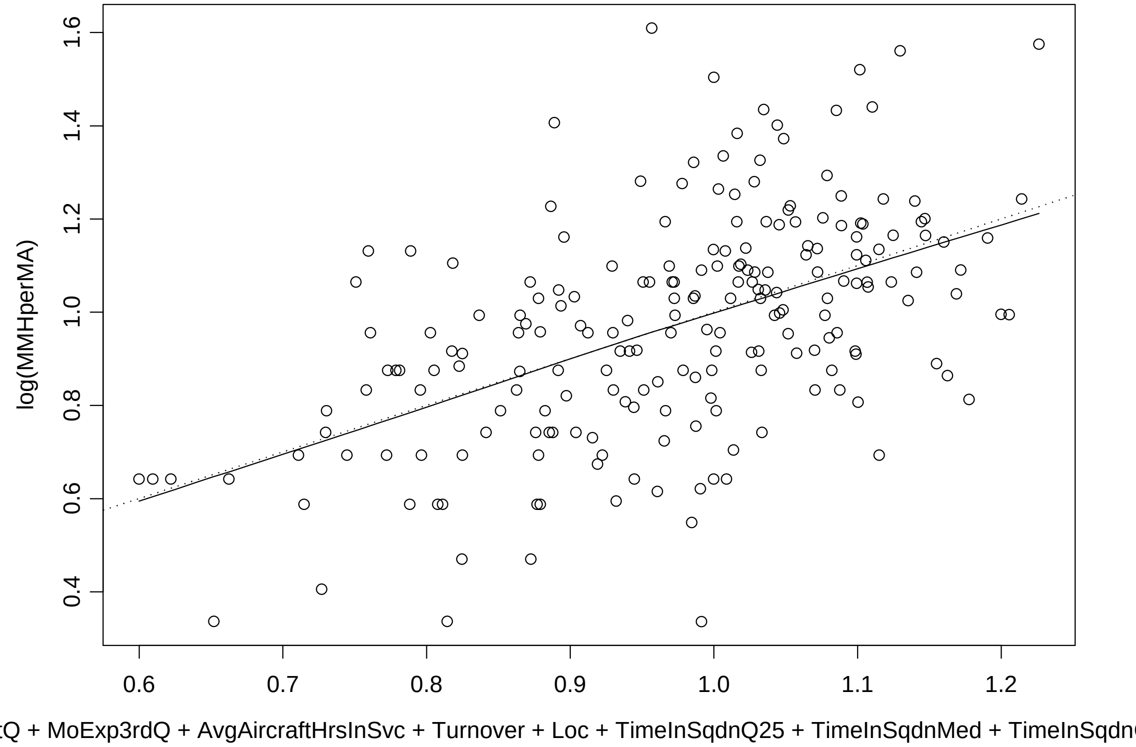

Figure E-2. Plot of Response vs Fitted Values, Full Model.

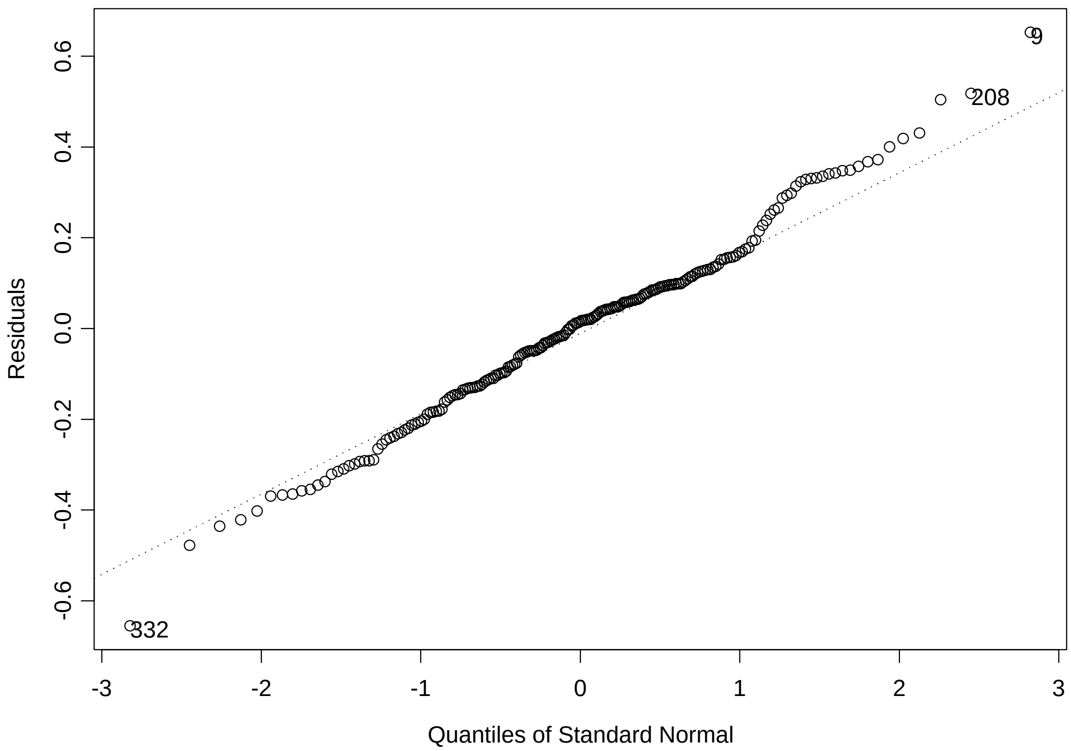

Figure E-3. Quantile-Quantile Plot of the Residuals, Full Model.

```
      *** Linear Model ***

Call: lm(formula = log(MMHperMA) ~ TEC + MoExp1stQ + MoExp3rdQ +
AvgAircraftHrsInSvc + Turnover + Loc + TimeInSqdnQ25 + TimeInSqdnMed +
       TimeInSqdnQ75 + Deployment + Flthrs + MoExp2ndQ, data = A, na.action =
na.exclude)
Residuals:
     Min      1Q  Median     3Q    Max
 -0.6554 -0.1302 0.01567 0.1086 0.6526

Coefficients:
                      Value Std. Error t value Pr(>|t|)
        (Intercept)  1.2280  0.2453     5.0060  0.0000
             TECAMAF  0.0517  0.0708     0.7304  0.4660
             TECAMAG  0.1865  0.0816     2.2861  0.0233
           MoExp1stQ  0.0011  0.0071     0.1620  0.8715
           MoExp3rdQ -0.0026  0.0022    -1.1800  0.2395
AvgAircraftHrsInSvc  0.0001  0.0000     1.7798  0.0767
            Turnover -0.2300  0.2191    -1.0497  0.2952
                 Loc  0.2214  0.0389     5.6884  0.0000
       TimeInSqdnQ25  0.0005  0.0065     0.0815  0.9351
       TimeInSqdnMed -0.0179  0.0057    -3.1402  0.0020
       TimeInSqdnQ75 -0.0090  0.0071    -1.2650  0.2074
       DeploymentUDP -0.1124  0.0512    -2.1929  0.0295
       DeploymentCVN  0.1827  0.1099     1.6634  0.0978
      DeploymentIRAQ  0.0680  0.2092     0.3249  0.7456
              Flthrs  0.0000  0.0001     0.2025  0.8397
           MoExp2ndQ  0.0064  0.0072     0.8896  0.3748

Residual standard error: 0.212 on 194 degrees of freedom
Multiple R-Squared: 0.2791
F-statistic: 5.007 on 15 and 194 degrees of freedom, the p-value is 2.751e-008
194 observations deleted due to missing values

Analysis of Variance Table

Response: log(MMHperMA)

Terms added sequentially (first to last)
                     Df Sum of Sq  Mean Sq  F Value      Pr(F)
                TEC   2  0.286042 0.143021  3.18082 0.0437273
          MoExp1stQ   1  0.342736 0.342736  7.62253 0.0063176
          MoExp3rdQ   1  0.050081 0.050081  1.11381 0.2925676
AvgAircraftHrsInSvc   1  0.068887 0.068887  1.53205 0.2173005
           Turnover   1  0.010424 0.010424  0.23183 0.6307150
                Loc   1  1.589110 1.589110 35.34216 0.0000000
      TimeInSqdnQ25   1  0.007769 0.007769  0.17278 0.6781147
      TimeInSqdnMed   1  0.570940 0.570940 12.69784 0.0004608
      TimeInSqdnQ75   1  0.010226 0.010226  0.22743 0.6339737
         Deployment   3  0.403538 0.134513  2.99159 0.0321322
             Flthrs   1  0.001517 0.001517  0.03374 0.8544627
          MoExp2ndQ   1  0.035585 0.035585  0.79142 0.3747722
          Residuals 194  8.722932 0.044964
```

Figure E-4. Full Model Summary and ANOVA Table, S-Plus Report

APPENDIX F
STEPWISE REDUCED MODEL

$$\ln Y_{s,t} = \beta_0 + \beta_1 X_{1,s,t} + \beta_2 X_{2,s,t} + \beta_3 X_{3,s,t} + \beta_4 X_{4,s,t} + \beta_5 X_{5,s,t} + \varepsilon_{s,t}$$

$Y_{s,t} =$ man-hours per maintenance action, squadron s, month t
$X_{1,s,t} =$ type equipment code
$X_{2,s,t} =$ average aircraft hours in service
$X_{3,s,t} =$ location
$X_{4,s,t} =$ months in squadron, median
$X_{5,s,t} =$ deployment status
$\varepsilon_{s,t} =$ residual
$k =$ number of variables
$s =$ squadron
$t =$ month

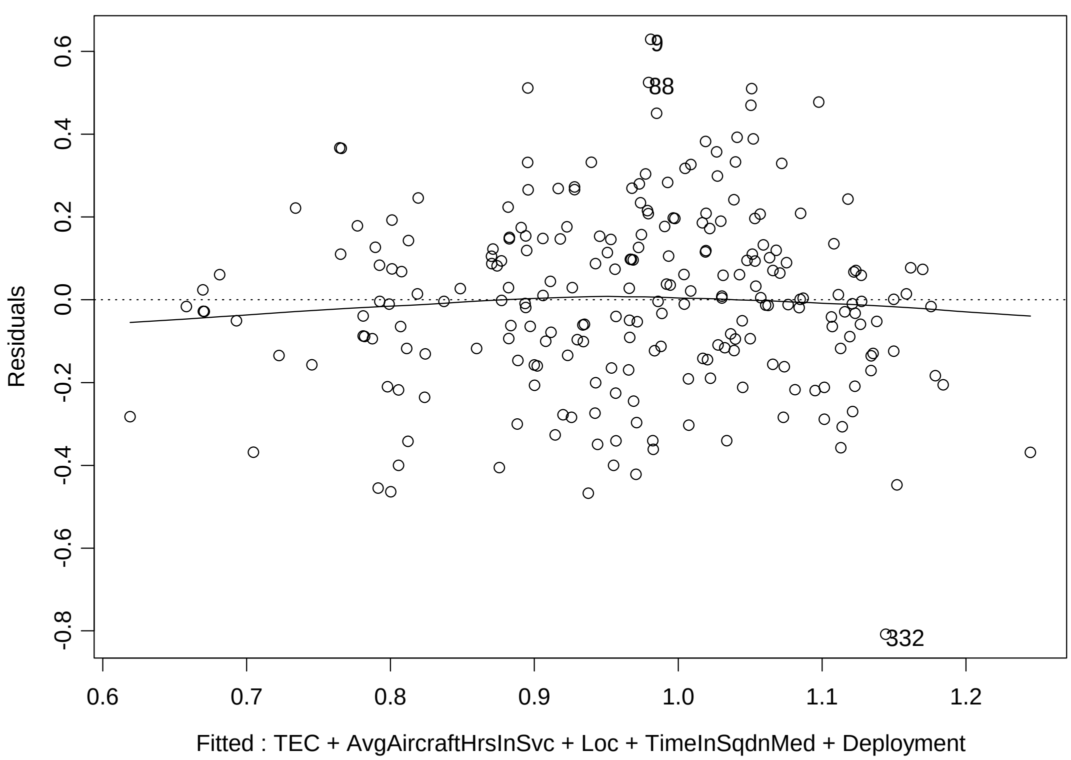

Figure F-1. Reduced Model and Plot of Residuals vs Fitted Values

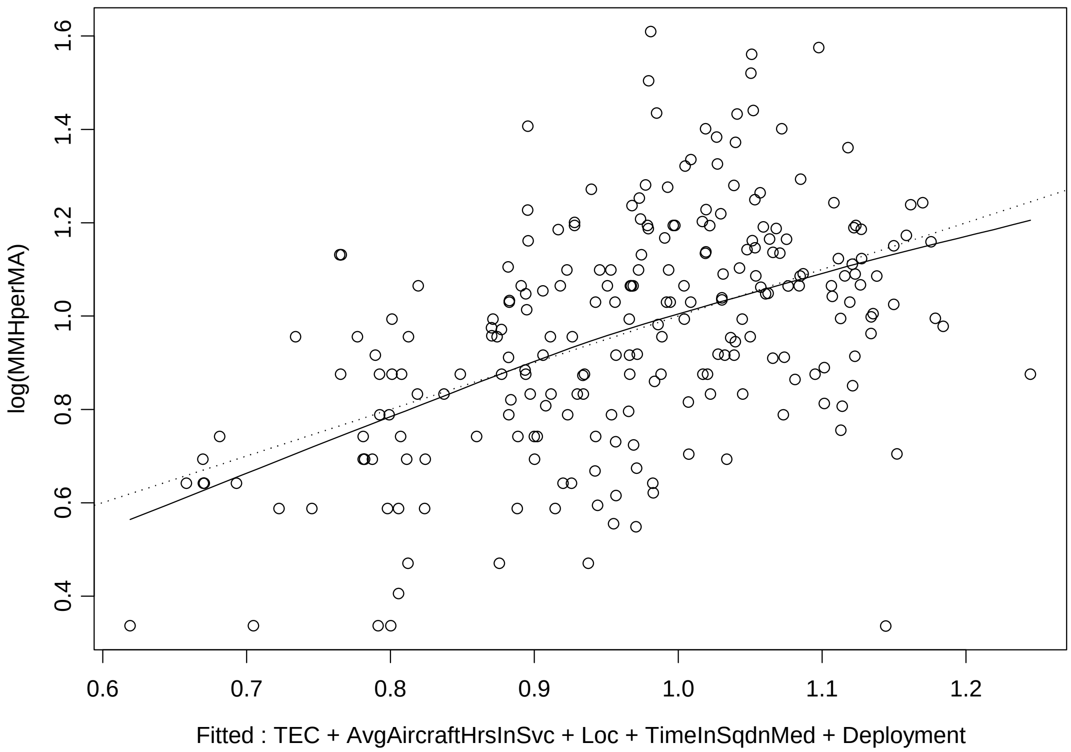

Figure F-2. Response vs Fitted Values, Reduced Model.

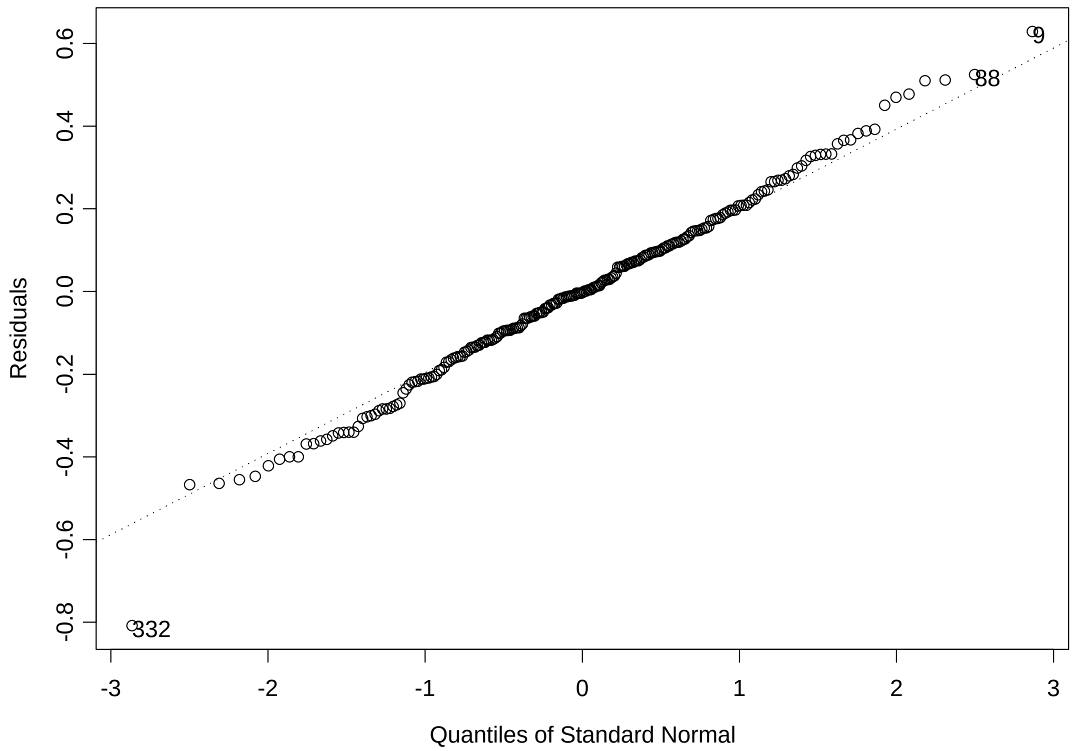

Figure F-3. Quantile-Quantile Plot of the Residuals, Reduced Model.

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APPENDIX G
FINAL MODEL

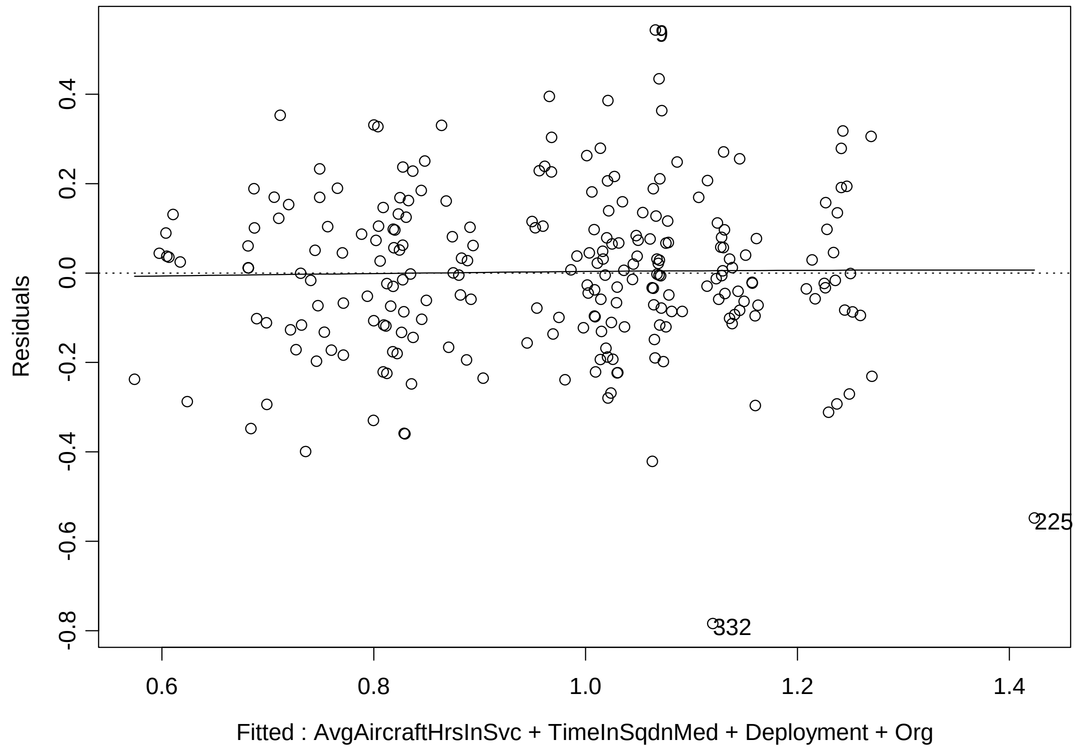

Figure G-1. Plot of Residuals vs Fitted Values, Final Model.

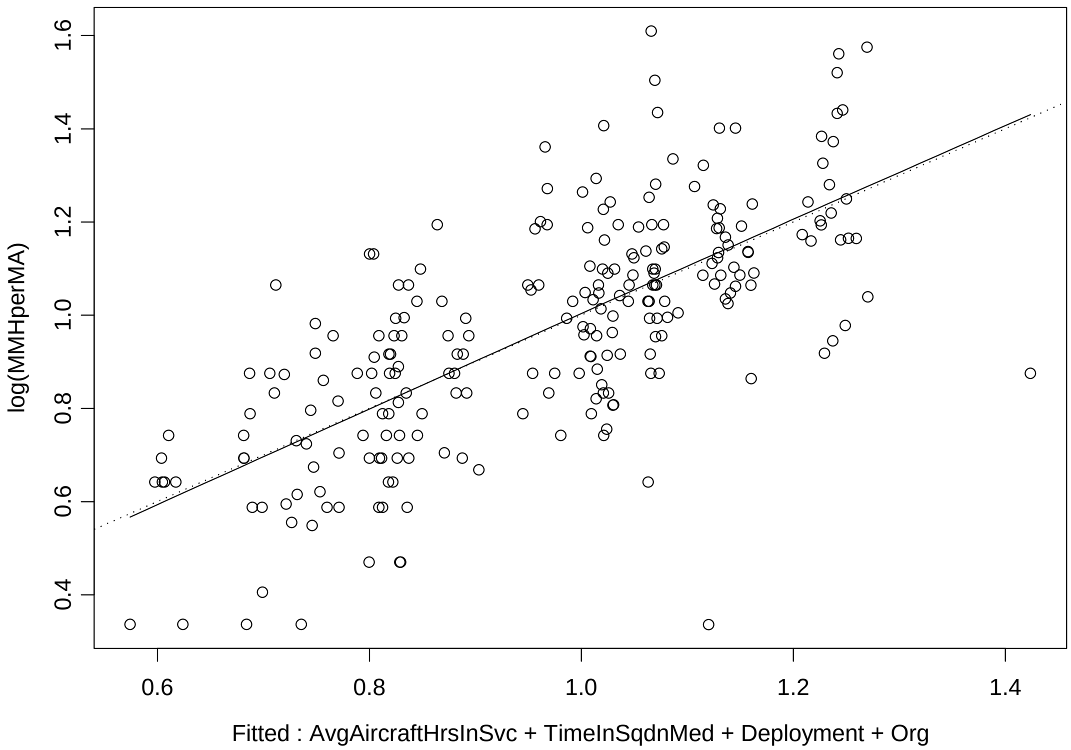

Figure G-2. Plot of Response vs Fitted Values, Final Model.

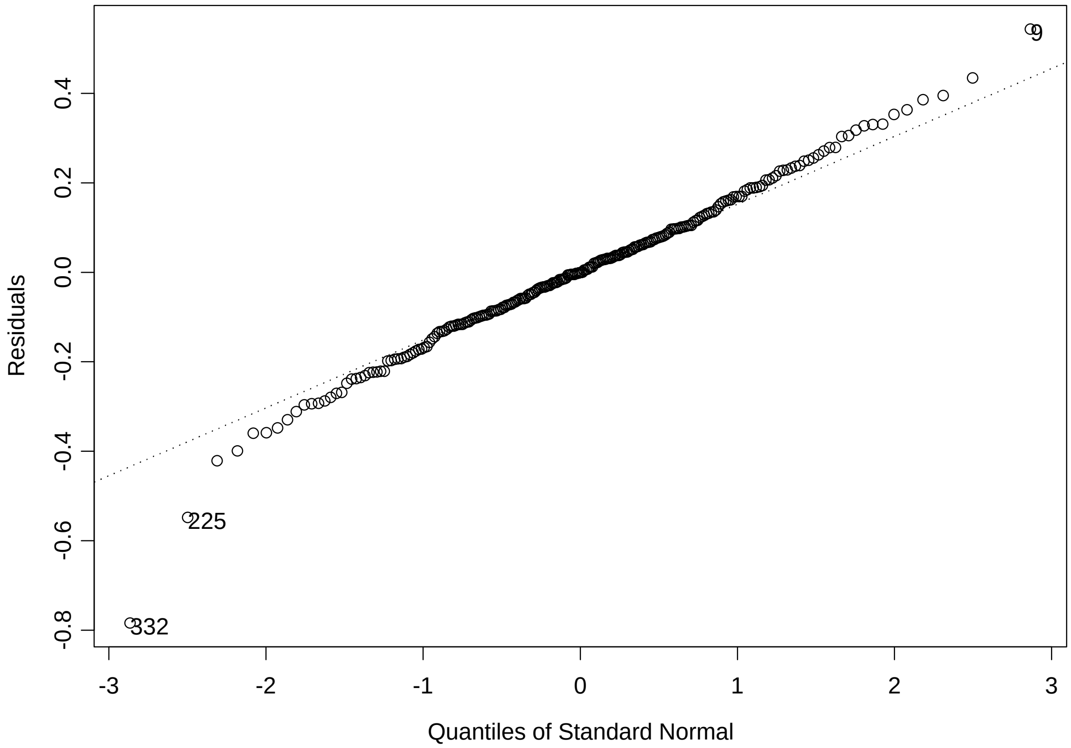

Figure G-3. Quantile-Quantile Plot of the Residuals, Final Model

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